

Integral resource capacity planning for inpatient care services based on hourly bed census predictions

N. Kortbeek¹²³⁴, A. Braaksma¹²³, H.F. Smeenk¹²,
P.J.M. Bakker², R.J. Boucherie¹³

¹Center for Healthcare Operations Improvement and Research (CHOIR),
University of Twente, Drienerlolaan 5, 7500 AE Enschede, The Netherlands.

²Department of Quality and Process Innovation, Academic Medical Center Amsterdam,
Meibergdreef 9, 1105 AZ Amsterdam, The Netherlands.

³Stochastic Operations Research, Department of Applied Mathematics,
University of Twente, Drienerlolaan 5, 7500 AE Enschede, The Netherlands.

⁴n.kortbeek@utwente.nl

Abstract

The design and operations of inpatient care facilities are typically largely historically shaped. A better match with the changing environment is often possible, and even inevitable due to the pressure on hospital budgets. Effectively organizing inpatient care requires simultaneous consideration of several interrelated planning issues. Also, coordination with upstream departments like the operating theater and the emergency department is much-needed. We present a generic analytical approach to predict bed census on nursing wards by hour, as a function of the Master Surgical Schedule (MSS) and arrival patterns of emergency patients. Along these predictions, insight is gained on the impact of strategic (i.e., case mix, care unit size, care unit partitioning), tactical (i.e., allocation of operating room time, misplacement rules), and operational decisions (i.e., time of admission/discharge). The method is used in the Academic Medical Center Amsterdam as a decision support tool in a complete redesign of the inpatient care operations.

Keywords: Probability, Health service, Hospitals, Medical care units, Bed occupancy, Surgical Scheduling

Introduction

Inpatient care facilities provide care to hospitalized patients by offering a room, a bed and board (PubMed 2012). Societal developments and budget constrains demand hospitals to on the one hand increase quality of care and on the other hand efficiency (RVZ 2012). This entails a strong incentive to reconsider the design and operations of inpatient care services. Since the 1950s, the application of operational research methods yields significant

contributions in accomplishing essential efficiency gains in health care delivery (Hulshof et al. 2011). In this paper, we present an exact method to assist hospital management in adequately organizing their inpatient care services.

Effectively designing inpatient care services requires simultaneous consideration of several interrelated strategic and tactical planning issues (Hulshof et al. 2011). Given service mix and case mix decisions, hospital management has to decide on care unit partitioning (which care units are created and which patient groups are assigned to these units) and care unit size (the number of staffed beds per care unit). Since the inpatient care facility is a downstream department, the outflow of the operating theater and the emergency department, are main drivers behind its workload. Therefore, it is highly desirable to apply coordinated planning: considering the inpatient care facility in isolation yields suboptimal decision making (Harper 2002, Vanberkel et al. 2010a). While smoothing patient inflow prevents large differences between peak and off-peak periods, and so realizes a more efficient use of resources (Adan et al. 2009, Harper 2002, Vissers et al. 2007), the authority of inpatient care facilities on their admission control is limited. Although the control on the inflow of patients from the emergency department is inherently very limited due to its nature, anticipation for emergency admissions is possible, by statistically predicting the arrival process of emergency patients that often follows a cyclic pattern (Green and Nguyen 2001). Anticipation for elective surgical patients is possible as well, by taking the surgical schedule into account (Adan et al. 2009, Green and Nguyen 2001, Harper 2002, Vissers et al. 2007). Hospitals typically allocate operating room capacity through a Master Surgical Schedule (MSS), a (cyclic) block schedule that allocates operating time capacity among patient groups (Fei et al. 2010, Guerriero and Guido 2010, Van Oostrum et al. 2008). In this paper, we address these various patient flows and take the necessity of integral decision making into account.

The challenge in decision making for inpatient care delivery is to guarantee care from appropriately skilled nurses and required equipment to patients with specific diagnoses, while making efficient use of scarce resources (Harper et al. 2005, Villa et al. 2009). Performance measures are required that reflect efficiency and quality of care to assess the quality of logistical layout. Efficiency is often expressed in high bed occupancy, which is assumed to imply efficient use of staff and other equipment (Gorunescu et al. 2002, Ridge et al. 1998). The drawback of high bed occupancy is that it may cause congestion, which manifests itself in two main consequences, both being a threat to the provided quality of care (Goulding et al. 2012, Green and Nguyen 2001): (i) patients may have to be rejected for admission due to lack of bed capacity, so-called admission refusals or rejections, (ii) patients may (temporarily) be placed in less appropriate units, so-called misplacements (Costa et al. 2003, Harper and Shahani 2002, Harrison et al. 2005). Due to such misplacements, planning decisions regarding a specific care unit can affect the operations of other units (Akkerman and Knip 2004, Cochran and Bharti 2006, Li et al. 2009). Planning of the inpatient care facility should not only take into account the upstream departments, but also the interrelationship between care units.

Previous analytical studies have addressed partial resource capacity planning issues within the inpatient care chain, for example by dimensioning care units in isolation (e.g. Bekker and De Bruin 2010, Gorunescu et al. 2002, Green and Nguyen 2001), balancing bed utilization across multiple units (e.g. Akcali et al. 2006, Cochran and Bharti 2006, Li et al. 2009), or focussing on improving the MSS to balance inpatient care demand (e.g. Adan et al. 2009, Bekker and Koeleman 2011, Beliën et al. 2009, Van Oostrum et al. 2008, Vanberkel et al. 2010b). More integral approaches can be found in simulation studies (e.g. Harper 2002, Harper and Shahani 2002, Troy and

Rosenberg 2009, Vanberkel and Blake 2007). The advantage of such approaches is their flexibility and therefore modeling power. However, the disadvantage is that the nature of such studies is typically context-specific, which limits the generalizability of application and findings.

We present a generic exact analytical approach to achieve the required integral and coordinated resource capacity planning decision-making for inpatient care services. The method builds upon the approach presented in Vanberkel et al. (2010b), which determines the workload placed on hospital departments by describing demand for elective inpatient care beds on a daily level as a function of the MSS. Based on a cyclic arrival pattern of emergency patients and an MSS block schedule of surgical patients, we derive demand predictions on an hourly level for several inpatient care units simultaneously for both acute and elective patients. (The method is also applicable for departments catering for non-surgical elective patients, as these can be incorporated in our model via fictitious OR blocks). This hourly level of detail is required to adequately incorporate the time-dependent behavior of the inpatient care process. Based on overflow rules we translate the demand predictions to bed census predictions, since demand and census may differ due to rejections and misplacements. The combination of the hourly level perspective and the bed census conversion enables us to derive several performance measures, along which the effectiveness of different logistical configurations can be assessed. In addition, what-if questions can be addressed considering the impact of operational interventions such as shortening length of stay or changing the times of admissions and discharges.

During the upcoming years the presented method will be applied in a Dutch teaching hospital, the Academic Medical Center (AMC) in Amsterdam in supporting the intended complete redesign of the inpatient care facility. As part of the total redesign, in the case study of the present article we restrict ourselves to a set of interrelated (with respect to capacity planning) specialties: traumatology, orthopedics, plastic surgery, urology, vascular surgery, and general surgery. By means of this case study we illustrate the practical potential of our analytical approach for logistical redesign of inpatient care services.

This paper is organized as follows. First, we describe the model consisting of demand predictions, bed census predictions and performance measures. The next section introduces the case study at the AMC and describes the numerical results. The paper closes with a discussion of our findings and opportunities for further research.

Predictive model

In this section, the model is described that predicts the workload at several care units of an inpatient care facility on a time scale of hours, due to patients originating from the operating theater and emergency department. The basis for the operating room outflow prediction is the MSS. The basis for the emergency department outflow prediction is a cyclic random arrival process which we define as the Acute Admission Cycle (AAC). Schematically, the approach is as follows. First, the impact of the MSS and the AAC are separately determined and then combined to obtain the overall steady state impact of the repeating cycles. Second, the obtained demand distributions are translated to bed census distributions. Finally, performance measures are formulated based on the demand and census distributions.

The operation of the inpatient care facility is as follows. Each day is divided in time intervals, which in principle can be regarded as hours (but could also resemble for example two- or four-hour time intervals). Patient admissions

are assumed to take place independently at the start of a time interval. Elective patients are admitted to a care unit either on the day before or on the day of surgery. For acute patients we assume a cyclic (e.g. weekly) non-homogeneous Poisson arrival process corresponding to the unpredictable nature of emergency arrivals. Discharges take place independently at the end of a time interval. For elective patients we assume the length of stay to depend only on the type of patient and to be independent of the day of admission and the day of discharge. For acute patients the length of stay and time of discharge are dependent on the day and time of arrival, in particular to account for possible disruptions in diagnostics and treatment during nights and weekends.

For the demand predictions, for both elective and acute patients three steps are performed. First, the impact of a single patient type in a single cycle (MSS or AAC) is determined, by which in the second step the impact of all patient types within a single cycle can be calculated. Then, since the MSS and AAC are cyclical, the predictions from the second step are overlapped to find the overall steady state impact of the repeating cycles. The workload predictions for elective and acute patients are combined to find the probability distributions of the number of recovering patients at the inpatient care facility on each unique day in the cycle which we denote as the Inpatient Facility Cycle (IFC). The length of the IFC is the least common multiple of the lengths of the MSS and the AAC.

Patient admission requests may have to be rejected due to a shortage of beds, or patients may (temporarily) be placed in less appropriate units. As a consequence, demand predictions and bed census predictions do not coincide. Therefore, an additional step is required to translate the demand distributions into census distributions. This translation is performed by assuming that after a misplacement the patient is transferred to his preferred care unit when a bed becomes available, where we assume a fixed patient-to-ward allocation policy, which prescribes the prioritization of such transfers.

Demand predictions for elective patients

Model input.

Time. An MSS is a repeating blueprint for the surgical schedule of S days. Each day is divided in T time intervals. Therefore, we have time points $t = 0, \dots, T$, in which $t = T$ corresponds to $t = 0$ of the next day.

For each single patient, day n counts the number of days before or after surgery, i.e., $n = 0$ indicates the day of surgery.

MSS utilization. For each day $s \in \{1, \dots, S\}$, a (sub)specialty j can be assigned to an available operating room i , $i \in \{1, \dots, I\}$. The OR block at operating room i on day s is denoted by $b_{i,s}$, and is possibly divided in a morning block $b_{i,s}^m$ and an afternoon block $b_{i,s}^a$, if an OR day is shared. The discrete distributions c^j represent how specialty j utilizes an OR block, i.e. $c^j(k)$ is the probability of k surgeries performed in one block, $k \in \{0, 1, \dots, C^j\}$. If an OR block is divided in a morning OR block and an afternoon OR block, c_M^j and c_A^j represent the utilization probability distributions respectively. For brevity, we do not include shared OR blocks in our formulation, since these can be modeled as two separate (fictitious) operating rooms.

Admissions. With probability e_n^j , $n \in \{-1, 0\}$, a patient of type j is admitted on day n . Given that a patient is admitted on day n , the time of admission is described by the probability distribution $w_{n,t}^j$. We assume that a patient who is admitted on the day of surgery is always admitted before or at time ϑ_j ; therefore, we have $w_{0,t}^j = 0$ for $t = \vartheta_j + 1, \dots, T - 1$.

Discharges. $P^j(n)$ is the probability that a type j patient stays n days after surgery, $n \in \{0, \dots, L^j\}$. Given that a patient is discharged on day n , the probability of being discharged in time interval $[t, t + 1)$ is given by $m_{n,t}^j$. We assume that a patient who is discharged on the day of surgery is discharged after time ϑ_j , i.e. $m_{0,t}^j = 0$ for $t = 0, \dots, \vartheta_j$.

Single surgery block. In this first step we consider a single specialty j operating in a single OR block. We compute the probability $h_{n,t}^j(x)$ that n days after carrying out a block of specialty j , at time t , x patients of the block are still in recovery. Note that admissions can take place during day $n = -1$ and during day $n = 0$ until time $t = \vartheta_j$. Discharges can take place during day $n = 0$ from time $t = \vartheta_j + 1$ and during days $n = 1, \dots, L^j$. Therefore, we calculate $h_{n,t}^j(x)$ as follows:

$$h_{n,t}^j(x) = \begin{cases} a_{n,t}^j(x) & , n = -1 \text{ and } n = 0, t \leq \vartheta_j, \\ d_{n,t}^j(x) & , n = 0, t > \vartheta_j \text{ and } n = 1, \dots, L^j, \end{cases}$$

where $a_{n,t}^j(x)$ represents the probability that x patients are admitted until time t on day n , and $d_{n,t}^j(x)$ is the probability that x patients are still in recovery at time t on day n . The derivations of $a_{n,t}^j$ and $d_{n,t}^j$ are presented in Appendix A.1.

Single MSS cycle. Now, we consider a single MSS in isolation. From the distributions $h_{n,t}^j$, we can determine the distributions $H_{m,t}$, the discrete distributions for the total number of recovering patients at time t on day m ($m \in \{0, 1, 2, \dots, S, S + 1, S + 2, \dots\}$) resulting from a single MSS cycle (see Appendix A.2).

Steady state. In this step, the complete impact of the repeating MSS is considered. The distributions $H_{m,t}$ are used to determine the distributions $H_{s,t}^{SS}$, the steady state probability distributions of the number of recovering patients at time t on day s of the cycle ($s \in \{1, \dots, S\}$) (see Appendix A.3).

Demand predictions for acute patients

Model input.

Time. The AAC is the repeating cyclic arrival pattern of acute patients with a length of R days. For each single patient, day n counts the number of days after arrival.

Admissions. An acute patient type is characterized by patient group p , $p = 1, \dots, P$, arrival day r and arrival time θ , which is for notational convenience denoted by type $j = (p, r, \theta)$. The Poisson arrival process of patient type j has arrival rate λ^j .

Discharges. $P^j(n)$ is the probability that a type j patient stays n days, $n \in \{0, \dots, L^j\}$. Given that a patient is discharged at day n , the probability of being discharged in time interval $[t, t + 1)$ is given by $\tilde{m}_{n,t}^j$. By definition, $\tilde{m}_{0,t}^j = 0$ for $t \leq \theta$.

Single patient type. In this first step we consider a single patient type j . We compute the probability $g_{n,t}^j(x)$ that on day n at time t , x patients are still in recovery. Admissions can take place during time interval $[\theta, \theta + 1)$ on day $n = 0$ and discharges during day $n = 0$ after time θ and during days $n = 1, \dots, L^j$. Therefore, we calculate $g_{n,t}^j(x)$ as follows:

$$g_{n,t}^j(x) = \begin{cases} \tilde{a}_t^j(x) & , n = 0, t = \theta, \\ \tilde{d}_{n,t}^j(x) & , n = 0, t > \theta \text{ and } n = 1, \dots, L^j, \end{cases}$$

where $\tilde{a}_t^j(x)$ represents the probability that x patients are admitted in time interval $[t, t + 1)$ on day $n = 0$, and $\tilde{d}_{n,t}^j(x)$ is the probability that x patients are still in recovery at time t on day n . The derivations of \tilde{a}_t^j and $\tilde{d}_{n,t}^j$ are presented in Appendix B.1.

Single cycle. Now, we consider a single AAC in isolation. From the distributions $g_{n,t}^j(x)$, we can determine the distributions $G_{w,t}$, the distributions for the total number of recovering patients at time t on day w ($w \in \{1, \dots, R, R + 1, R + 2, \dots\}$) resulting from a single AAC (see Appendix B.2).

Steady state. In this step, the complete impact of the repeating AAC is considered. The distributions $G_{w,t}$ are used to determine the distributions $G_{r,t}^{SS}$, the steady state probability distributions of the number of recovering patients at time t on day r of the cycle ($r \in \{1, \dots, R\}$) (see Appendix B.3).

Demand predictions per care unit

To determine the complete demand distribution of both elective and acute patients, we need to combine the steady state distributions $H_{s,t}^{SS}$ and $G_{r,t}^{SS}$. In general, the MSS cycle and AAC are not equal in length, i.e. $S \neq R$. This has to be taken into account when combining the two steady state distributions. Therefore, we define the new IFC length $Q = LCM(S, R)$, where the function LCM stands for *least common multiple*. Let $Z_{q,t}$ be the probability distribution of the total number of patients recovering at time t on day q during a time cycle of length Q :

$$Z_{q,t} = H_{q \bmod S + S \cdot \mathbb{1}(q \bmod S = 0), t}^{SS} \otimes G_{q \bmod R + R \cdot \mathbb{1}(q \bmod R = 0), t}^{SS},$$

where \otimes denotes the discrete convolution function. Let W^k be the set of specialties j whose operated patients are (preferably) admitted to unit k ($k \in \{1, \dots, K\}$) and V^k the set of acute patient types j that are (preferably) admitted to unit k . Then, the demand distribution for unit k , $Z_{q,t}^k$, can be calculated by only considering the patients in W^k in equation (A.1) and V^k in equation (B.1).

Bed census predictions

We translate the demand distributions $Z_{q,t}^k$, $k = 1, \dots, K$, into bed census distributions $\hat{Z}_{q,t}$, the distributions of the number of patients present in each unit k at time t on day q . To this end, we require an allocation policy ϕ that uniquely specifies from a demand vector $\mathbf{x} = (x_1, \dots, x_K)$ a bed census vector $\hat{\mathbf{x}} = (\hat{x}_1, \dots, \hat{x}_K)$, in which x_k and \hat{x}_k denote the demand for unit k and the bed census at unit k , respectively. Let $\phi(\cdot)$ be the function that executes allocation policy ϕ . Let $\hat{Z}_{q,t}^k$ denote the marginal distribution of the census at unit k given by distribution $\hat{Z}_{q,t}$. With M_k the capacity of unit k in number of beds, we obtain

$$\hat{Z}_{q,t}(\hat{\mathbf{x}}) = \left(\hat{Z}_{q,t}^1(\hat{x}_1), \dots, \hat{Z}_{q,t}^K(\hat{x}_K) \right) = \sum_{\{\mathbf{x} | \hat{\mathbf{x}} = \phi(\mathbf{x})\}} \left\{ \prod_{k=1}^K Z_{q,t}^k(x_k) \right\}.$$

We do not impose restrictions on the allocation policy ϕ other than specifying a unique relation between demand \mathbf{x} and census configuration $\hat{\mathbf{x}}$. Recall that the underlying assumption is that a patient is transferred to his preferred unit when a bed becomes available. The policy ϕ also reflects the priority rules that are applied for such transfers. As an illustration, we present an example for an inpatient care facility with two care units of capacity M_1 and

M_2 respectively:

$$\phi(\mathbf{x}) = \begin{cases} (x_1, x_2) & , x_1 \leq M_1, x_2 \leq M_2, \\ (M_1, \min\{x_2 + (x_1 - M_1), M_2\}) & , x_1 > M_1, x_2 \leq M_2, \\ (\min\{x_1 + (x_2 - M_2), M_1\}, M_2) & , x_1 \leq M_1, x_2 > M_2, \\ (M_1, M_2) & , x_1 > M_1, x_2 > M_2. \end{cases} \quad (1)$$

Under this policy patients are assigned to their bed of preference if available, and are otherwise misplaced to the other unit if beds are available there.

Performance indicators

Based on the demand distributions $Z_{q,t}^k$ and the census distributions $\hat{Z}_{q,t}^k$ we are able to formulate a variety of performance indicators. We present a selection of such performance indicators, which will be used in the next section to evaluate the impact of different scenarios and interventions.

Demand percentiles. Let $D_{q,t}^k(\alpha)$ be the α -th percentile of demand at time t on day q :

$$D_{q,t}^k(\alpha) = \min_x \left\{ \sum_{i=0}^x Z_{q,t}^k(i) \geq \alpha \right\}.$$

(Off-)Peak demand. Reducing peaks and drops in demand will balance bed occupancy and therefore allows more efficient use of available staff and beds. Define $\bar{P}_q^k(\alpha)$ ($\underline{P}_q^k(\alpha)$) and $\bar{P}^k(\alpha)$ ($\underline{P}^k(\alpha)$) to be the maximum (minimum) α -th demand percentile per day and over the complete cycle respectively:

$$\begin{aligned} \bar{P}_q^k(\alpha) &= \max_t \left\{ D_{q,t}^k(\alpha) \right\}, & \bar{P}^k(\alpha) &= \max_q \left\{ \bar{P}_q^k(\alpha) \right\}, \\ \underline{P}_q^k(\alpha) &= \min_t \left\{ D_{q,t}^k(\alpha) \right\}, & \underline{P}^k(\alpha) &= \min_q \left\{ \underline{P}_q^k(\alpha) \right\}. \end{aligned}$$

Admission rate. Patient admissions may increase the nursing workload. Let $\Lambda_{q,t}^k$ be the distribution of the number of arriving patients during time interval $[t, t+1)$ on day q who are preferably admitted to care unit k . To obtain $\Lambda_{q,t}^k$, we first determine $\bar{a}_{n,t}^j$, the distribution of the number of elective type j arrivals during time interval $[t, t+1)$ on day n ($n \in \{-1, 0\}$):

$$\bar{a}_{n,t}^j(x) = \sum_{y=0}^C c^j(y) \bar{a}_{n,t}^j(x|y) \quad , \quad \text{with} \quad \bar{a}_{n,t}^j(x|y) = \binom{y}{x} (e_n^j w_{n,t}^j)^x (1 - e_n^j w_{n,t}^j)^{y-x}.$$

$\Lambda_{q,t}^k$ is then determined by taking the discrete convolution over all relevant arrival distributions of both elective and acute patient types:

$$\Lambda_{q,t}^k = \left\{ \bigotimes_{i=1}^I \left\{ \bigotimes_{j \in W^k: j \in b_{i,s'}} \bar{a}_{-1,t}^j \right\} \otimes \left\{ \bigotimes_{j \in W^k: j \in b_{i,s''}} \bar{a}_{0,t}^j \right\} \right\} \otimes \left\{ \bigotimes_{j \in V^k: r=r'} \bar{a}_t^j \right\}. \quad (2)$$

where $s' = 1 + q \bmod S$, $s'' = q \bmod S + S \cdot \mathbf{1}_{(q \bmod S=0)}$, $r' = q \bmod R + R \cdot \mathbf{1}_{(q \bmod R=0)}$, and $\bigotimes_{x \in \mathcal{X}} f_x$ denotes the discrete convolution over the probability distributions $f_x, x \in \mathcal{X}$. The first term in the right-hand side of (2) represents the elective patients who claim a bed at unit k ($j \in W^k$), who are operated in any OR and who are admitted on the day $s' - 1$ before surgery or on the day s'' of surgery. The second term in the right-hand side of (2) represents the acute patients who claim a bed at unit k ($j \in V^k$) and who arrive on the corresponding day r' in the AAC.

Average bed occupancy. Let $\rho_{q,t}^k$, ρ_q^k , ρ^k be the average number of beds occupied at care unit k respectively at time t on day q , on day q , and over the complete cycle:

$$\rho_{q,t}^k = \frac{1}{M^k} \sum_{x=0}^{M^k} x \cdot \hat{Z}_{q,t}^k(x), \quad \rho_q^k = \frac{1}{T} \sum_{t=0}^{T-1} \rho_{q,t}^k, \quad \rho^k = \frac{1}{Q} \sum_{q=1}^Q \rho_q^k.$$

Rejection probability. Let $R^{\phi,k}$ denote the probability that under allocation policy ϕ an admission request of an arriving patient for unit k has to be rejected, because all beds at unit k are already occupied and none of the alternative beds (prescribed by ϕ) are available. To determine $R^{\phi,k}$, we first determine $R_{q,t}^{\phi,k}$: the probability of such an admission rejection at time t on day q . $R^{\phi,k}$ is then calculated as follows:

$$R^{\phi,k} = \frac{1}{\sum_{q,t} E[\Lambda_{q,t}^k]} \sum_{q,t} E[\Lambda_{q,t}^k] R_{q,t}^{\phi,k}.$$

Let n indicate the number of arriving patients who are preferably admitted to unit k , and $\mathbf{x} = (x_1, \dots, x_K)$ the demand for each unit (in which these arrivals are already incorporated). Introduce $\mathcal{R}^{\phi,k}(\mathbf{x}, n)$, the number of rejected patients under allocation policy ϕ of the n arriving patients to unit k , and $Z_{q,t}^k(x_k|n)$ the probability that at time t on day q in total x_k patients demand a bed at unit k and n of them have just arrived. Then, $R_{q,t}^{\phi,k}$ is calculated by:

$$\begin{aligned} R_{q,t}^{\phi,k} &= \frac{E[\# \text{ rejections at unit } k \text{ on time } (q, t)]}{E[\# \text{ arrivals to unit } k \text{ on time } (q, t)]} \\ &= \frac{1}{E[\Lambda_{q,t}^k]} \sum_{\mathbf{x}} \prod_{\ell \neq k} Z_{q,t}^{\ell}(x_{\ell}) \sum_n \mathcal{R}^{\phi,k}(\mathbf{x}, n) \Lambda_{q,t}^k(n) Z_{q,t}^k(x_k|n). \end{aligned} \quad (3)$$

The derivation of $Z_{q,t}^k(x_k|n)$ is presented in Appendix C. $\mathcal{R}^{\phi,k}(\mathbf{x}, n)$ is uniquely determined by allocation policy ϕ . For example, for the case with $K = 2$ presented in (1), we have for unit $k = 1$:

$$\mathcal{R}^{\phi,1}(\mathbf{x}, n) = \begin{cases} \min\{n, x_1 - M_1\} & , x_1 \geq M_1, x_2 \geq M_2, \\ \max\{0, (x_1 - M_1) - (M_2 - x_2)\} & , x_1 \geq M_1, x_2 < M_2, n \geq (x_1 - M_1), \\ n - \max\{0, \min\{n, (M_2 - x_2 - [x_1 - M_1 - n])\}\} & , x_1 \geq M_1, x_2 < M_2, n < (x_1 - M_1), \\ 0 & , \text{otherwise.} \end{cases} \quad (4)$$

In (4), the first case reflects the situation in which all beds at care unit 2 are occupied so that all arriving patients who do not fit in unit 1 have to be rejected. The second and third case reflect the situation that (some of) the arriving patients can be misplaced to unit 2 so that only a part of the arriving patients have to be rejected. In the second case, the $(x_1 - M_1)$ patients that do not fit at unit 1 are all arriving patients. In the third case, some of the $(x_1 - M_1)$ patients were already present so that not all $(M_2 - x_2)$ beds at unit 2 can be used to misplace arriving patients.

Misplacement probability. Let $M^{\phi,k}$ denote the probability that under allocation policy ϕ a patient who is preferably admitted to care unit k is admitted to another unit. The derivation of $M^{\phi,k}$ is equivalent to that of $R^{\phi,k}$. In (3), $\mathcal{R}^{\phi,k}(\mathbf{x}, n)$ has to be replaced by $\mathcal{M}^{\phi,k}(\mathbf{x}, n)$, which gives the number of misplaced patients under allocation policy ϕ of the n arriving patients to unit k and which is again uniquely determined by ϕ . Observe that for the two unit example presented in (1), we have:

$$\mathcal{M}^{\phi,1}(\mathbf{x}, n) = \begin{cases} \min\{x_1 - M_1, M_2 - x_2\} & , x_1 > M_1, x_2 < M_2, n \geq (x_1 - M_1), \\ \max\{0, \min\{n, (M_2 - x_2 - [x_1 - M_1 - n])\}\} & , x_1 > M_1, x_2 < M_2, n < (x_1 - M_1), \\ 0 & , \text{otherwise.} \end{cases}$$

Productivity. Let \mathcal{K} be a set of cooperating care units, i.e., units that mutually allow misplacements. Let $\mathcal{P}^{\mathcal{K}}$ reflect the productivity of the available capacity at care units $k \in \mathcal{K}$, defined as the number of patients that is treated per bed per year:

$$\mathcal{P}^{\mathcal{K}} = \frac{365}{Q} \frac{1}{\sum_{k \in \mathcal{K}} M^k} \sum_{k \in \mathcal{K}} \sum_{q,t} (1 - R_{q,t}^{\phi,k}) E[\Lambda_{q,t}^k] \quad (5)$$

Remark 1 (Approximation). *Observe that the calculations of misplacements and rejections are an abstract approximation of complex reality. In our model, we count each time interval how many of the arriving patients have to be misplaced or rejected. Since we do not remove rejected patients from the demand distribution, it is likely that we overestimate the rejection and misplacement probabilities. However, also in reality strict rejections are often avoided: by postponing elective admissions, predischarging another patient, or letting acute patients wait at the emergency department. These are all undesired degradations of provided quality of care. Therefore, our method provides a secure way of organizing inpatient care services. It is applicable to evaluate performance for care unit capacities that give low rejection probabilities, thus when high service levels are desired, which is typically the case in healthcare.*

Remark 2 (Numerical evaluation). *Recall that to compute all performance measures formulated above it is only required to specify the input parameters that were specified under the headers ‘model input’ for the elective and the acute patients.*

Results

The case study entails the university hospital AMC, which has 20 operating rooms, and 30 inpatient departments with in total 1000 beds. Due to both economic and medical developments, the AMC is forced to reorganize the operations of the inpatient services during the upcoming years. On the basis of an example for six surgical specialties, this section illustrates the potential of the presented method to direct these reorganizations.

Case study

As an example, we take the following specialties into account: traumatology (TRA), orthopedics (ORT), plastic surgery (PLA), urology (URO) vascular surgery (VAS), and general surgery (GEN). In the present setting, the patients of the mentioned specialties are admitted in four different inpatient care departments. Care unit A houses GEN and URO, unit B VAS and PLA, unit C TRA, and unit D ORT. The physical building is such that units A and B are physically adjacent (Floor I), so are units C and D (Floor II). For these specialties, we have historical data available over 2009-2010 on 3498 (5025) elective (acute) admissions, with an average length-of-stay (LOS) of 4.85 days (see Table 1). Currently, no cyclical MSS is applied. Each time, roughly six weeks in advance the MSS is determined for a period of four weeks. The capacities of units A, B, C, and D are 32, 24, 24, and 24 beds, respectively. However, it often happens that not all beds are available, due to personnel shortages. The utilizations over 2009-2010 were 53.2%, 55.6%, 54.4%, and 60.6% (which includes some patients of other than the given specialties that were placed in these care units). These utilizations reflect administrative bed census, which means the percentage of time that a patient physically occupies a bed, or keeps it reserved during the time the patient is at the operating theater or at the intensive care department. Unfortunately, no confident data was available on rejections and misplacements.

Validation

We have estimated the input parameters for our model based on historical data of 2009-2010 from the hospital electronic databases. The event logs of the operating room and inpatient care databases had to be matched. Since the data contained many errors, extensive cleaning was required. Patients of other specialties who stayed at departments A-D have been deleted. Since no cyclical MSS was applied in practice, we set the MSS length on two years, following the surgery blocks as occurred in practice during 2009-2010. Elective surgery blocks are only executed on weekdays. For the elective patient types, the distributions for the number of surgeries and for the admission/discharge processes are estimated per specialty. We set the length of the AAC on one week. For the acute patients, the discharge distributions are estimated per specialty, and to have enough measurements, via the following clustering: admission time intervals 0–8, 8–18, and 18–24. Furthermore, for all patient types the discharge distributions during a day are assumed to be equal for the days $n \geq 2$.

As an illustration, Figure 1 displays the model results for demand distributions $Z_{q,t}^k$ for care unit A on Wednesdays against the historical data. The results are similar for the other days and the other care units. Slight differences can be observed for (1) the elective patients on Sunday afternoon, since in practice Sunday-admission times differ from weekdays, where we assume the same admission time distributions for all days, and (2) the elective patients on Friday afternoon, since in practice more patients are discharged just before the weekend, where we assume the length-of-stay distributions to be independent of the day of surgery. We conclude that our model is a valid representation of the AMC practice.

Analysis

We consider several interventions which potentially improve the efficiency of the inpatient care service operations. For the interventions that are based on the current MSS, we run the model for the estimated two-year MSS, and we calculate the performance measures only over the second year, to account for warm-up effects. To assess the effects of the interventions, we first evaluate the performance of a base case scenario, the situation that most closely resembles current practice. The base case takes the current capacities, misplacements take place between care units A and B (Floor I), and between units C and D (Floor II). We assume that the available beds are always open, so no ad-hoc closings are allowed. Note that the calculated rejection and misplacement percentages are therefore most likely an underestimation of current practice (of which no reliable data is available). The productivity measure is calculated per floor, since the misplacement policy implies that capacity is ‘shared’ per

Specialty	Acronym	Care unit	Elective admissions	Acute admissions	Average LOS (in days)	Load (# patients)
General surgery	GEN	A	611	901	3.31	6.88
Urology	URO	A	818	1157	3.68	9.99
Vascular surgery	VAS	B	257	634	8.30	10.16
Plastic surgery	PLA	B	639	288	2.29	2.91
Traumatology	TRA	C	337	1200	5.88	12.41
Orthopedics	ORT	D	836	845	6.23	14.38

Table 1: Overview historical data 2009-2010.

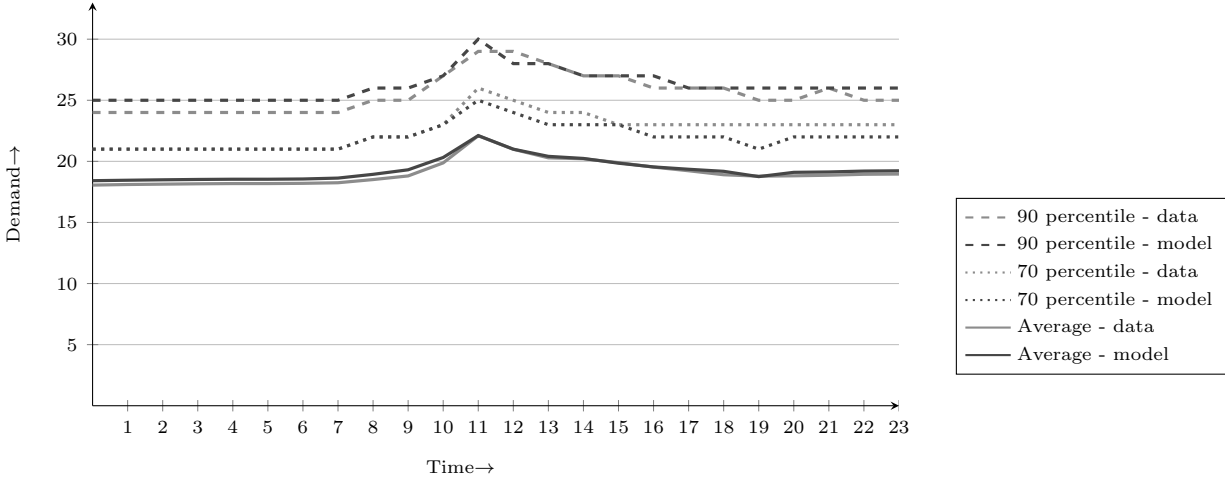


Figure 1: Validation of the model results against historical data (Wednesday, care unit A).

floor. The following interventions are considered, of which the results are displayed in Tables 2-4:

(1) **Rationalize bed requirements.** The current numbers of beds are a result of historical development. Given particular service requirements, which are to be specified by the hospital, we determine whether the number of beds can be reduced to achieve a higher bed utilization while a certain quality level is guaranteed. We consider rejection probabilities not exceeding 5%, 2.5%, and 1%. Often, there are different bed configurations with the same total number of beds per floor, satisfying a given maximum rejection probability. Per floor, from the available configurations the one is chosen that gives the lowest maximum misplacement probability. It can be seen that a significant reduction in the number of beds is possible. However, the overall bed utilizations are still modest, because demand drops during weekend days when no elective surgeries take place. In addition, there is a correlation between moments of higher census and moments that patients arrive, which leads to higher rejection probabilities compared to for instance a stationary Poisson arrival process. The hospital recognizes that simultaneously prohibiting bed closings on an ad-hoc basis and downsizing the total number of beds is more effective in realizing a consistent quality-of-service level, whilst it is also more efficient (reflected by the clear increase in the productivity measure, i.e., the number of patients that can be treated per bed per day).

(2) **No misplacements.** For the purpose of insight, in this intervention we explore what would happen if no misplacements were allowed. By abandoning misplacements, we demonstrate the benefits of capacity pooling when overflow between care units is allowed. These benefits are due to the so-called portfolio effect which induces that the relative variability in demand is reduced by economies of scale.

It can be concluded that in our case units in the order of size 20-30 beds are too small to operate efficiently in isolation.

(3) **Change operational process.** First, hospital management proposes to admit all elective patients on the day of surgery, since admitting patients the day before surgery is often induced by logistical reasons and not by medical necessity. Second, to reduce census peaks during the middle of the day, management proposes to aim for discharges to happen before noon. To predict the potential impact of these changes in the

Intervention	Unit	Capacity (# beds)	Rejection (%)	Misplace (%)	Utilization (%)	Floor	Capacity (# beds)	Productivity (eq.(5))	Productivity ($\Delta\%$)	
<i>Base case</i>	A	32	0.14	1.85	56.9	}	AB	56	50.0	-
	B	24	0.08	1.22	56.5					
	C	24	0.03	0.45	55.6	}	CD	48	35.1	-
	D	24	0.10	3.68	61.5					
<i>1. Rationalize bed requirements</i>										
Rejection < 5%	A	27	4.92	6.07	67.7	}	AB	45	59.3	+18.6
	B	18	4.59	14.35	74.3					
	C	18	3.42	8.90	74.0	}	CD	38	42.5	+21.1
	D	20	4.92	11.72	73.3					
Rejection < 2.5%	A	28	2.31	5.86	65.0	}	AB	48	57.2	+14.4
	B	20	1.67	7.30	67.7					
	C	18	2.02	10.30	73.3	}	CD	40	41.3	+17.5
	D	22	2.27	6.14	67.5					
Rejection < 1%	A	29	0.94	5.00	62.6	}	AB	51	54.5	+9.1
	B	22	0.52	3.15	61.8					
	C	20	0.54	4.39	66.5	}	CD	43	39.0	+11.0
	D	23	0.79	4.93	64.3					
<i>2. No misplacements</i>										
Rejection < 5%	A	30	4.22	-	60.5	}	AB	52	51.7	+3.5
	B	22	3.67	-	61.5					
	C	20	4.93	-	66.1	}	CD	44	36.7	+4.4
	D	24	3.78	-	61.5					
Rejection < 2.5%	A	32	2.00	-	56.8	}	AB	55	49.9	-0.2
	B	23	2.22	-	58.9					
	C	22	1.67	-	60.3	}	CD	47	35.2	+0.1
	D	25	2.42	-	59.1					
Rejection < 1%	A	34	0.86	-	53.5	}	AB	59	47.1	-5.7
	B	25	0.73	-	54.2					
	C	23	0.91	-	57.8	}	CD	50	33.4	-4.8
	D	27	0.90	-	54.8					

Table 2: The numerical results for the base case, intervention 1, and intervention 2 (with the productivity- $\Delta\%$ relative to the base case).

operational process, we adjust the admission distributions of elective patients, so that admissions on the day before surgery are postponed to time $t = 8$ on the day of surgery (which impacts 81.9% of the elective patients), and we adjust the discharge distributions of days $n \geq 1$, so that discharges later than time $t = 11$ are moved forward to $t = 11$ (which impacts 51.8% of the total patient population).

Compared to intervention 1 the number of beds can be further decreased. Also, the results indicate that hospitals should not only focus on achieving high bed utilizations: although somewhat lower utilization is achieved, productivity is significantly increased.

- (4) **Balance MSS.** The realized MSS created artificial demand variability. This intervention estimates the potential of a cyclical MSS that is designed with the purpose to balance bed census. We constructively created a cyclical MSS with a length of four weeks. First, for each specialty, an integer number of OR blocks is chosen so that an output is achieved similar to the original MSS; due to this integrality average demand

Intervention	Unit	Capacity (# beds)	Rejection (%)	Misplace (%)	Utilization (%)	Floor	Capacity (# beds)	Productivity (eq.(5))	Productivity ($\Delta\%$)	
<i>3. Change operational process</i>										
Rejection < 5%	A	24	4.51	9.24	66.4	}	AB	43	62.5	+25.2
	B	19	3.03	6.53	66.1					
	C	17	3.65	11.21	74.3	}	CD	37	43.6	+24.2
		D	20	5.00	9.12					
Rejection < 2.5%	A	26	2.31	5.22	61.7	}	AB	45	60.9	+21.8
	B	19	2.03	7.54	65.7					
	C	17	2.11	12.74	73.8	}	CD	39	42.3	+20.5
		D	22	2.28	4.62					
Rejection < 1%	A	27	0.94	4.44	59.3	}	AB	48	57.9	+15.8
	B	21	0.64	3.26	59.7					
	C	19	0.58	5.59	66.8	}	CD	42	39.9	+13.6
		D	23	0.83	3.78					
<i>4. Balance MSS</i>										
Rejection < 5%	A	25	4.85	8.43	74.5	}	AB	44	62.5	+25.0
	B	19	3.93	8.73	74.4					
	C	18	3.24	8.84	74.6	}	CD	38	43.5	+23.7
		D	20	3.99	10.03					
Rejection < 2.5%	A	27	2.25	4.29	69.5	}	AB	46	61.1	+22.3
	B	19	2.41	10.25	73.9					
	C	19	1.46	6.21	70.8	}	CD	40	42.1	+19.9
		D	21	1.86	7.50					
Rejection < 1%	A	28	0.83	3.57	66.7	}	AB	49	58.3	+16.6
	B	21	0.66	4.32	67.4					
	C	20	0.60	4.05	67.3	}	CD	42	40.5	+15.3
		D	22	0.79	5.21					
<i>5. Combination (1), (3), and (4)</i>										
Rejection < 5%	A	23	4.92	9.17	70.9	}	AB	42	65.5	+31.1
	B	19	3.47	5.56	68.9					
	C	17	3.77	11.04	74.9	}	CD	37	44.5	+26.5
		D	20	4.21	7.34					
Rejection < 2.5%	A	25	2.28	4.72	65.7	}	AB	44	64.0	+28.0
	B	19	2.18	6.85	68.4					
	C	18	1.74	7.87	71.0	}	CD	39	43.1	+22.7
		D	21	2.02	5.54					
Rejection < 1%	A	26	0.82	3.90	63.1	}	AB	47	60.8	+21.7
	B	21	0.57	2.75	62.2					
	C	19	0.74	5.21	67.5	}	CD	41	41.4	+18.0
		D	22	0.89	3.87					

Table 3: The numerical results for interventions 2, 3 and 4 (with the productivity- $\Delta\%$ relative to the base case).

is slightly increased. Second, these blocks have been manually divided over the days in the MSS, and by trial-and-error a balanced outflow was realized.

As an illustration, Figure 2 displays the average bed utilization per weekday for care unit A (rejection probability <1%) before and after balancing the MSS. From this figure it is clear that both the midweek peak and the weekend dip can be cleared to a large extent, which results in distinct efficiency gains (see Table 3).

We have reason to believe that even larger gains can be achieved. First, by developing a structured method

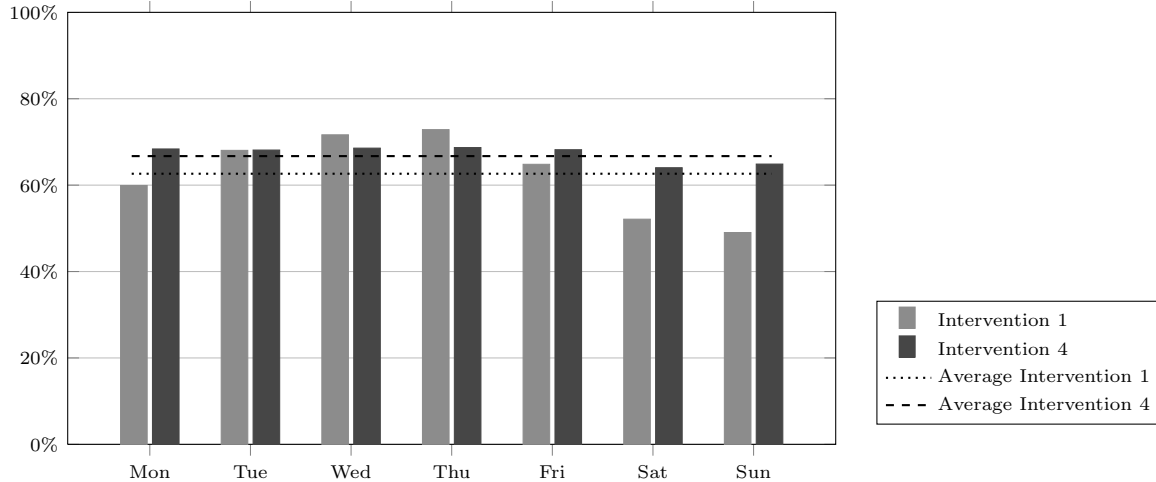


Figure 2: Average bed utilization per weekday (care unit A, rejections < 1%).

to optimize the MSS instead of manual optimization. Second, the lack of detail in the available historical MSS data resulted in high variation in the input probability distributions of the number of cases per OR block and the length-of-stay distributions. When more information would be available on the content of MSS blocks, for instance on the level of subspecialty or even surgery type, the census predictions would show lower variability, resulting in lower bed requirements.

- (5) **Combination 1, 3, and 4.** This intervention combines interventions (1), (3), and (4). Hospital management agreed upon a service level norm of rejection probabilities <2.5%. Under this requirement, it is possible to reduce the number of beds by 20% (from 104 to 83), and increase productivity by roughly 25%. Considering that the AMC has 30 inpatient departments, the savings potential for the entire hospital is substantial.
- (6) **Separation elective and acute.** This intervention illustrates the capability of the model to provide quantitative support in decision making on care unit partitioning. Clinicians and managers in the AMC discuss the desirability to split elective and acute patient flows. Intervention 6a is formulated such that all elective patients are treated at Floor I (unit A: GEN, URO, VAS; unit B: PLA, TRA, ORT) and all acute patients at Floor II (unit C: GEN, URO, VAS, PLA; unit D: TRA, ORT). In intervention 6b splitting electives and acute patients is combined with creating a balanced MSS, and intervention 6c extends this by including the changes in the operational process from intervention 3. Table 4 shows that the logistical performance is similar to the previous care unit configuration. We conclude therefore that whether or not to separate elective and acute patients in the studied case, should mainly be decided based on medical arguments.

Discussion

The design and operations of inpatient care facilities are typically to a large extent historically shaped. Accomplishing a better match with the changing environment is often possible, and even inevitable due to the pressure on hospital budgets. As an illustration, Dutch hospitals observe a shift from inpatient to outpatient care as a

Intervention	Unit	Capacity (# beds)	Rejection (%)	Misplace (%)	Utilization (%)	Floor	Capacity (# beds)	Productivity (eq.(5))	Productivity ($\Delta\%$)	
<i>6a. Separation elective and acute</i>										
Rejection < 5%	A	21	4.36	10.34	68.9	}	AB	42	45.0	-
	B	21	4.00	7.65	68.9					
	C	21	3.92	7.82	70.3	}	CD	42	57.6	-
		D	21	3.89	11.12					
Rejection < 2.5%	A	22	2.40	8.31	66.0	}	AB	44	43.7	-
	B	22	2.30	6.04	65.9					
	C	22	2.03	6.00	67.0	}	CD	44	56.1	-
		D	22	1.99	8.41					
Rejection < 1%	A	24	0.80	4.43	60.7	}	AB	47	41.6	-
	B	23	0.95	4.87	62.9					
	C	23	0.98	4.33	64.0	}	CD	46	54.2	-
		D	23	0.95	6.02					
<i>6b. Combination (6a) and balance MSS</i>										
Rejection < 5%	A	21	3.35	6.70	73.6	}	AB	41	48.9	+8.7
	B	20	3.30	8.55	75.7					
	C	21	3.92	7.82	70.3	}	CD	42	57.6	0.0
		D	21	3.89	11.12					
Rejection < 2.5%	A	22	2.07	4.33	70.6	}	AB	42	48.2	+10.3
	B	20	2.44	9.41	75.5					
	C	22	2.03	6.00	67.0	}	CD	44	56.1	0.0
		D	22	1.99	8.41					
Rejection < 1%	A	23	0.65	3.25	67.2	}	AB	45	45.8	+10.2
	B	22	0.59	3.90	69.2					
	C	23	0.98	4.33	64.0	}	CD	46	54.4	0.0
		D	23	0.95	6.02					
<i>6c. Combination (6b) and change operational process</i>										
Rejection < 5%	A	19	4.00	7.01	68.7	}	AB	39	51.3	+14.1
	B	20	3.07	4.46	66.4					
	C	20	4.73	9.59	71.8	}	CD	41	58.8	+2.0
		D	21	3.74	9.29					
Rejection < 2.5%	A	20	2.46	4.59	65.5	}	AB	40	50.6	+15.6
	B	20	2.38	5.16	66.2					
	C	22	2.10	4.62	65.9	}	CD	43	57.3	+2.2
		D	21	2.20	10.82					
Rejection < 1%	A	21	0.77	3.55	62.4	}	AB	43	47.9	+15.2
	B	22	0.56	2.04	60.3					
	C	23	0.78	3.60	62.6	}	CD	46	54.4	+0.2
		D	23	0.67	5.21					

Table 4: The numerical results for intervention 6 (with the productivity- $\Delta\%$ relative to 6a).

result of technological developments and increased medical knowledge. Consequently, many of these hospitals are organized in many care units that slowly decrease in size. Low bed utilizations occur, while at the same time a national shortage of nursing staff is observed. Therefore, the majority of Dutch hospitals is reorganizing its inpatient clinic. In this paper, we have presented a generic analytical method that can support logistical decision-making for inpatient care services, by quantitatively predicting the impact of different scenarios and interventions.

We are able to assist decision-making on various planning levels. Insight can be gained on the impact of

strategic (i.e. capacity dimensioning, case mix), tactical (i.e. the allocation of operating room time, misplacement rules), and operational decisions (i.e. time of admission/discharge). For these decisions, rules-of-thumb can be established. For example, we have shown the economies-of-scale effect: larger facilities can operate under a higher occupancy level than smaller ones in trying to achieve a given patient service level, since randomness balances out. In addition, by allowing overflow and setting appropriate rules, the benefits of bed capacity pooling are utilized, while the placement of patients on the preferred ward is maximized. Also, by adjusting the surgical schedule, extremely busy and quiet periods can be avoided. Once such basic rules are obtained, explicit interventions can be formulated of which the effect can be predicted. This combination between basic insights and quantifications is highly valuable to hospital managers.

The method is currently being applied in the AMC in redesigning its inpatient care services, of which the improvement potential is substantial (as numerically illustrated in this paper). Such a process of drastically changing an existing health care environment is highly political. We believe that the benefit of quantitative analysis in such a ‘negotiation’ process is that it rationalizes the process of realizing a good trade-off between interests of clinicians and patients. Quantification ensures that robust organizational plans are formulated, for instance also anticipating for the expected increase of acute admissions due to a changing nature of the emergency department. Finally, we observe that applying the method and discussing the results triggers the discussion to also focus on other potential gains like a more efficient use of the operating theater.

The development of a user-friendly decision support tool (DSS) based on our method will be a next step in achieving practical impact. Our model relies on data which is easily extractable from typical hospital management systems. This makes it possible to automate the process of collecting the required input parameters to run the model. Integration with the hospital management system, visualization of the results, and the possibility to run what-if scenarios will be desired specifications of the DSS.

In future research we will focus on three directions. First, by combining the current inpatient census with the settled upcoming MSS, the model could be exploited to support last minute decision-making like whether or not to hire temporary staff. Second, we will focus on incorporating the possibility of intermediate intensive care unit stays for patients who have undergone a complex surgery. Finally, the hourly level of the model will provide the basis for a formal approach along which effective and efficient nurse staffing can be achieved.

Appendix

In the appendix, the derivations are presented that were omitted in the main article for reasons of readability. Note that the exposition is such that it is supplementary to the main text, and is therefore not intended to be comprehensible in isolation.

A Demand predictions for elective patients

A.1 Single surgery block

To calculate $a_{n,t}^j(x)$, we first determine the admission process under a given number of performed surgeries y . Define $a_{n,t}^j(x|y)$ as the probability that x patients are admitted until time t on day n , given that y admissions

take place in total. Then:

$$a_{n,t}^j(x|y) = \begin{cases} \binom{y}{x} (v_{n,t}^j)^x (1 - v_{n,t}^j)^{y-x} & , n = -1, t = 0, \\ \sum_{g=0}^x \binom{y-g}{x-g} (v_{n,t}^j)^{x-g} (1 - v_{n,t}^j)^{y-x} a_{n-1, T-1}^j(g|y) & , n = 0, t = 0, \\ \sum_{g=0}^x \binom{y-g}{x-g} (v_{n,t}^j)^{x-g} (1 - v_{n,t}^j)^{y-x} a_{n, t-1}^j(g|y) & , n = -1, t = 1, \dots, T-1 \text{ and} \\ & n = 0, t = 1, \dots, \vartheta_j - 1, \\ 0 & , n = 0, t \geq \vartheta_j \end{cases}$$

where $v_{n,t}^j$ is the probability for a type j patient to be admitted in time t , given that he/she will be admitted at day n and is not yet admitted before t :

$$v_{n,t}^j = \frac{w_{n,t}^j e_n^j}{e_n^j \sum_{k=t}^{T-1} w_{n,k}^j + e_0^j \cdot \mathbf{1}_{(n=-1)}}.$$

Finally,

$$a_{n,t}^j(x) = \sum_{y=x}^{C^j} a_{n,t}^j(x|y) c^j(y).$$

To calculate $d_{n,t}^j(x)$, we first determine $d_n^j(x)$, for day 0 the probability that x patients are present at the start of the discharge process ($t = \vartheta_j$) and for days $n > 0$ the probability that x patients are present at the start of the day:

$$d_n^j(x) = \begin{cases} c^j(x) & , n = 0 \\ \sum_{g=x}^{C^j} \binom{g}{x} (s_{n-1}^j)^{g-x} (1 - s_{n-1}^j)^x d_{n-1}^j(g) & , n = 1, \dots, L^j, \end{cases}$$

where s_n^j is the probability that a type j patient who is still present at the begin of day n is discharged on day n :

$$s_n^j = \frac{P^j(n)}{\prod_{m=0}^{n-1} (1 - s_m^j)}.$$

Starting from $d_n^j(x)$, we determine the day process:

$$d_{n,t}^j(x) = \begin{cases} 0 & , n = 0, t < \vartheta_j, \\ d_n^j(x) & , n = 0, t = \vartheta_j \text{ and } n > 0, t = 0, \\ \sum_{k=x}^{C^j} \binom{k}{x} (z_{n,t-1}^j)^{k-x} (1 - z_{n,t-1}^j)^x d_{n,t-1}^j(k) & , n = 0, t > \vartheta_j \text{ and } n > 0, t > 0, \end{cases}$$

where $z_{n,t}^j$ is the probability of a type j patient to be discharged during time interval $[t, t+1)$ on day n , given this patient is still present at time t :

$$z_{n,t}^j = \frac{m_{n,t}^j P^j(n)}{P^j(n) \sum_{i=t}^{T-1} m_{n,i}^j + \sum_{k=n+1}^{L^j} P^j(k)}.$$

A.2 Single MSS cycle

We determine the overall probability distribution of the number of patients in recovery resulting from a single MSS, using discrete convolutions. If specialty j is assigned to OR block $b_{i,s}$, then the distribution $\bar{h}_{n,t}^{i,s}$ for the

number of recovering patients of block $b_{i,s}$ present at time t on day m ($m \in \{0, 1, 2, \dots, S, S+1, S+2, \dots\}$) is given by:

$$\bar{h}_{m,t}^{i,s} = \begin{cases} \mathbf{0} & , m < s-1 \\ h_{m-s,t}^j & , m \geq s-1 \end{cases}$$

where $\mathbf{0}$ means $\bar{h}_{m,t}^{i,s}(0) = 1$ and all other probabilities $\bar{h}_{m,t}^{i,s}(x), x > 0$ are 0. Then, $H_{m,t}$ is computed by:

$$H_{m,t} = \bar{h}_{m,t}^{1,1} \otimes \bar{h}_{m,t}^{1,2} \otimes \dots \otimes \bar{h}_{m,t}^{1,S} \otimes \bar{h}_{m,t}^{2,1} \otimes \dots \otimes \bar{h}_{m,t}^{I,S}. \quad (\text{A.1})$$

A.3 Steady state

Since the cyclic structure of the MSS implies that the recovery of patients receiving surgery during one cycle may overlap with patients from the next cycle, the distributions $H_{m,t}$ have to be overlapped in the correct manner.

$H_{s,t}^{SS}$ can be computed as follows:

$$H_{s,t}^{SS} = \begin{cases} H_{s,t} \otimes H_{s+S,t} \otimes \dots \otimes H_{s+\lceil M/S \rceil S,t} & , s = 1, \dots, S-1, \\ H_{0,t} \otimes H_{S,t} \otimes \dots \otimes H_{\lceil M/S \rceil S,t} & , s = S. \end{cases}$$

where $M = \max\{m \mid \exists t, x \text{ with } H_{m,t}(x) > 0\}$.

B Demand predictions for acute patient types

B.1 Single patient type

For patient type $j = (p, r, \theta)$, the admission process \tilde{a}_t^j is determined by a non-homogeneous Poisson process:

$$\tilde{a}_t^j(x) = \frac{(\lambda^j)^x e^{-\lambda^j}}{x!}, \quad t = \theta.$$

To calculate $\tilde{d}_{n,t}^j(x)$, we first determine $\tilde{d}_n^j(x)$, for day 0 the probability that x patients are present at the start of the discharge process ($t = \theta + 1$) and for days $n > 0$ the probability that x patients are present at the start of the day:

$$\tilde{d}_n^j(x) = \begin{cases} \tilde{a}_\theta^j(x) & , n = 0, \\ \sum_{g=x}^{\infty} \binom{g}{x} (\tilde{s}_{n-1}^j)^{g-x} (1 - \tilde{s}_{n-1}^j)^x \tilde{d}_{n-1}^j(g) & , n = 1, \dots, L^j, \end{cases}$$

where \tilde{s}_n^j is the probability that a type j patient who is still present at the begin of day n is discharged during day n :

$$\tilde{s}_n^j = \frac{P^j(n)}{\prod_{m=0}^{n-1} (1 - \tilde{s}_m^j)}.$$

Starting from \tilde{d}_n^j , we determine the day process:

$$\tilde{d}_{n,t}^j(x) = \begin{cases} 0 & , n = 0, t \leq \theta, \\ \tilde{d}_n^j(x) & , n = 0, t = \theta + 1 \text{ and } n > 0, t = 0, \\ \sum_{k=x}^{\infty} \binom{k}{x} (\tilde{z}_{n,t-1}^j)^{k-x} (1 - \tilde{z}_{n,t-1}^j)^x \tilde{d}_{n,t-1}^j & , n = 0, t > \theta + 1 \text{ and } n > 0, t > 0, \end{cases}$$

where $\tilde{z}_{n,t}^j$ is the probability of a type j patient to be discharged during time interval $[t, t + 1)$ on day n , given this patient is still present at time t :

$$\tilde{z}_{n,t}^j = \frac{\tilde{m}_{n,t}^j P^j(n)}{P^j(n) \sum_{i=t}^{T-1} \tilde{m}_{n,i}^j + \sum_{k=n+1}^{L^j} P^j(k)}.$$

B.2 Single cycle

To determine the overall probability distribution of the number of patients in recovery resulting from a single AAC, define $\bar{g}_{w,t}^j$ as the probability distribution of the number of recovering patients of type j present at time interval t on day w ($w \in \{1, 2, \dots, R, R + 1, R + 2, \dots\}$). The distribution $\bar{g}_{w,t}^j$ is given by:

$$\bar{g}_{w,t}^j = \bar{g}_{w,t}^{P,r,\theta} = \begin{cases} \mathbf{0} & , w < r, \\ g_{w-r,t}^j & , w \geq r. \end{cases}$$

Then, $G_{w,t}$ is computed by:

$$G_{w,t} = \bar{g}_{w,t}^{1,1,0} \otimes \dots \otimes \bar{g}_{w,t}^{1,1,T-1} \otimes \bar{g}_{w,t}^{1,2,0} \otimes \dots \otimes \bar{g}_{w,t}^{1,2,T-1} \otimes \bar{g}_{w,t}^{2,1,0} \otimes \dots \otimes \bar{g}_{w,t}^{P,R,T-1}. \quad (\text{B.1})$$

B.3 Steady state

$G_{r,t}^{SS}$ can be computed as follows:

$$G_{r,t}^{SS} = G_{r,t} \otimes G_{r+R,t} \otimes G_{r+2R,t} \otimes \dots \otimes G_{r+[W/R]R,t},$$

where $W = \max\{r \mid \exists t, x \text{ with } G_{r,t}(x) > 0\}$.

C Performance indicators

In this appendix, the derivation of $Z_{q,t}^k(x_k|n)$ is presented. To this end, let us first introduce the concept *cohort*. A cohort is a group of patients originating from a single instance of an OR block (electives) or admission time interval (acute patients). Then,

$$\begin{aligned} Z_{q,t}^k(x_k|n) &= \frac{P[\text{Demand } x_k \text{ patients for unit } k \text{ on time } t \text{ on day } q \text{ of which } n \text{ are arriving in } [t, t + 1)]}{P[n \text{ arrivals for unit } k \text{ on day } q \text{ in } [t, t + 1)]} \\ &= \frac{1}{\Lambda_{q,t}^k(n)} \sum_{\substack{y_{\sigma(1)}, \dots, y_{\sigma(\Omega)}, \\ n_{\sigma(1)}, \dots, n_{\sigma(\omega)}: \\ \sum_i y_i = x_k, \sum_j n_j = n}} \left\{ \prod_{i=\omega+1}^{\Omega} f_{q,t}^{\sigma(i)}(y_{\sigma(i)}) \right\} \left\{ \prod_{j=1}^{\omega} \alpha_{q,t}^{\sigma(j)}(y_{\sigma(j)}) \tilde{a}_{q,t}^{\sigma(j)}(n_{\sigma(j)} | y_{\sigma(j)}) \right\}, \end{aligned}$$

where Ω is the total number of cohorts, ω the number of cohorts that do generate arrivals during time interval $[t, t + 1)$ on day q , and the permutation σ is such that the patient types $\sigma(1), \dots, \sigma(\omega)$ are the types that can generate those arrivals. Further, for notational convenience we introduce the function $f_{q,t}^i$ as $f_{q,t}^i = h_{q,t}^i$ for the elective patients, and $f_{q,t}^i = g_{q,t}^i$ for acute patient types. Also, we introduce $\alpha_{q,t}^j$ as $\alpha_{q,t}^j = a_{q,t}^j$ for the elective patient types and $\alpha_{q,t}^j = \tilde{a}_t^{(p,q \bmod R + R \cdot \mathbf{1}_{q \bmod R=0,t})}$ for the acute patient types. It remains to define $\tilde{a}_{q,t}^j(n_j | y_j)$,

the probability that for an arriving cohort, from the y_j patients present in total, n_j arrivals occur during time interval $[t, t + 1)$:

$$\check{d}_{q,t}^j(n_j|y_j) = \binom{y_j}{n_j} (\nu_{n,t}^j)^{n_j} (1 - \nu_{n,t}^j)^{y_j - n_j},$$

where for elective patient types $\nu_{n,t}^j = \frac{w_{n,t}^j e_n^j}{e_n^j \sum_{k=0}^t w_{n,k}^j + e_{-1}^j \cdot \mathbb{1}_{(n=0)}}$ and for acute patient types $\nu_{n,t}^j = 1$.

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