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Research

Balancing Workload in the PACU by Using an Integrated OR Planning Methodology

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A B S T R A C T

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PACU resource optimization
flow shop scheduling

Purpose: The individual scheduling of the operating rooms (ORs) has a significant influence on postoperative care at hospital facilities. We studied the effect of incorporating postoperative departments in the decision process with regard to scheduling ORs and developed an integrated OR planning methodology that determines an optimal surgery sequence and postanesthesia care unit (PACU) nursing staff level, with the objective to level the variability in inflow of patients in the PACU.

Design: We developed an integrated OR planning methodology that investigates the sequencing of a surgical suite process with multiple ORs and postoperative hospital facilities.

Methods: This research was performed by representing a discrete-time two-stage flow shop problem. A retrospective study was performed in which the derived model was validated using discrete-event simulation.

Findings: Simulation results show that applying the integrated planning methodology decreased the variability in bed demand and smoothed the workload for the nursing staff in the PACU. Moreover, applying the algorithm led to a decrease in PACU completion time and a reduced amount of overtime hours for the surgical suite. Based on our results, we derived simple scheduling guidelines.

Conclusions: Our simulation results confirmed the hypothesis that prospectively sequencing ORs' cases can effectively decrease the variability in bed demand and smoothen the workload for the staff personnel. Moreover, applying the algorithm leads to a decrease in PACU completion time and less overtime hours for the surgical suite. As such, an integrated OR planning methodology facilitates hospitals in improving OR efficiency.

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Efforts to increase the efficiency of the hospital surgical sector have most often focused on improving operating room (OR) efficiency in terms of utilization, overtime, and on-time start performance. Surgical suites however function in synchrony with postoperative hospital units, such as the intensive care unit (ICU) and the postanesthesia care unit (PACU). Pursuing efforts to increase OR efficiency may therefore result in situations where postoperative departments experience significant fluctuations in inpatient admission.^{1,2} These fluctuating patient admissions result

in a suboptimal bed usage and peaks in workload for the nursing staff, which in turn, may have a detrimental impact on the quality of the care-giving process and impede the efficient patient flow.^{3–5}

Recent articles related to OR management seem to acknowledge the importance of an integrated OR planning process and suggest, among other things, to integrate available resources in the PACU, ICU, or ward as a downstream capacity constraint to prevent capacity shortages^{6–12}; for example, determine a cyclic surgery block schedule with the objective to minimize the expected bed shortage

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on the general ward in a given planning cycle. In another study, a similar approach was used, with the only objective of leveling the bed occupancy on the general ward.¹³

Another study aimed to level bed utilization in postoperative departments with the aid of surgical sequencing heuristics.^{1,6} The aim of both studies was to assess whether resequencing of surgeries in one OR at a time could affect the hourly number of patients receiving care in the PACU. Heuristics aimed at smoothing the inflow of patients in the PACU (eg, mixed & HiHd [half increase and half decrease in OR time]) resulted in less peaks in workload, as compared with an initial random case list.

Heydari and Soudi¹⁴ modeled their OR scheduling problem as a two-stage flexible flow shop, a variant of job shop scheduling. The proposed model investigated the sequencing of a surgical process with multiple ORs and the PACU, in which each patient had to pass through the two stages in consecutive order, with no waiting times between them. Although these assumptions held, their use of a makespan objective would most likely involve dense surgery schedules, hence resulting in peaks in bed demand.

Calegari et al¹⁵ modeled their OR scheduling problem as a hybrid flow shop, using the concept of break in moments, and the PACU as a downstream capacity constraint. Their usage of a break-in-moments objective would most likely reduce the variability in inflow of patients in the PACU; however, it does not necessarily smooth the bed occupancy rate nor the workload for the nursing staff in the PACU. This study seemed to adjust the aforementioned approach with the introduction of a nurse roster component and the usage of a different objective function and time representation.

In this study, we aimed to develop an integrated OR planning methodology that determines an optimal surgery sequence and PACU nursing staff level, with the objective to level the variability in inflow of patients to the PACU. We hypothesized, based on prior research¹ that prospectively resequencing ORs' cases can level the inflow of patients to the PACU, and as a result, improve the global performance of the ORs. On positioning our work, this study can be considered as a follow-up, as we aim to prospectively sequence multiple ORs' cases. Moreover, the study serves to further extend the work of others,^{6,7} who integrated the available resources in postoperative departments as downstream capacity constraints, hence focused predominantly on improving OR efficiency. Last, we aimed to adjust the flow shop scheduling approach¹⁴ with the introduction of a nurse roster component and the usage of a different objective function and time representation. To this end, using mixed integer linear programming (MILP), we first developed an integrated planning algorithm, which was subsequently validated with discrete event simulation on retrospective data from our operating theater.

Methods

The study was performed in a large nonacademic teaching hospital. The Medical Research Ethics Committees United approved the study and waived the requirements for written informed consent.

The data contained all surgical cases performed in 2016 for which an outflow to the PACU was recorded (eg, 15,995). After the removal of the surgical cases performed outside regular opening hours (eg, 7:00 to 18:00), a sample size of 14,295 cases was obtained as the input for further analysis. The data set included 29 variables containing relevant information regarding the monitoring of the surgery outline and the patient's stay in the PACU (Table 1).

Patient Categorization and Distribution Fitting

To increase the applicability of the proposed model for numerous health care institutions, uniform patient groups were

Table 1
Data Set Variables

No.	Variable Name
1	OR (name)
2	Emergency indication
3	Date
4	Time out
5	Debriefing
6	Surgical discipline
7	Plan code
8	CTG code
9	Treatment (name)
10	Search key
11	Call patient (time)
12	Arrival patient OR (time)
13	Administration of locoregional anesthesia (time)
14	Administration of antibiotic prophylaxis (time)
15	Start surgery (time)
16	Start induction (time)
17	Induction finished (time)
18	Start incision (time)
19	Incision finished (time)
20	Closure finished (time)
21	Call for transfer to postoperative department (time)
22	Transfer to general ward (time)
23	LOS (PACU)
24	ASA Physical Status Classification
25	Anesthesia (Ane) abbreviation
26	Anesthesia (Ane) technique
27	Estimated surgery duration
28	Total surgery duration
29	Net surgery duration

OR, operating room; CTG, College Tarteven Gezondheidszorg (Institute for Defining Health Care Prices); LOS, length of stay; PACU, postanesthesia care unit; ASA, American Society of Anesthesiologists.

derived by means of a prototype evaluation system in which group membership was dependent on the patient's priority indication, America Society of Anesthesiologists physical status classification, and planned surgery duration.^{16,17,18} Probability distribution fitting was performed to identify the stochastic distribution that was best suited to approximate the procedure times and length of stay (LOS) in the PACU for the identified uniform categories. The Allfitdist package in Matlab R2014b was used as a software tool to assess and compare the goodness of fit for a selection of parametric distributions on the basis of several fit metrics (eg, AIC [Akaike information criterion], AICc [AIC with a correction for finite sample sizes], BIC [Bayesian information criterion], Nlogl [Negative of the log likelihood]).¹⁹ A one-sample Kolmogorov Smirnov test was subsequently performed to confirm the obtained fit results.²⁰

Two-Stage Flow Shop Scheduling Problem

The conceptual scheduling problem investigates the sequencing of a surgical suite process with multiple ORs and postoperative units, including the PACU, which can be represented as a discrete-time and two-stage flow shop problem.^{14,21}

On adhering to the classical definition inherent to flow shop scheduling, a surgical case (job) can be considered as a sequence of processing steps to be performed using a dedicated set of hospital resources, where each case typically comprises two processing steps corresponding to the intraoperative and postoperative stages of the patient's hospital stay (Figure 1). The intraoperative hospitalization stage includes the transfer of the patient to the surgical suite, induction and emergence from anesthesia, and execution of the surgical intervention. The postoperative stage begins after the transfer of the patient to either the ICU, medium care (MC), coronary care unit (CCU), general ward, or PACU, where one is able to recover from the residual effects of anesthesia.²² Most patients are taken directly to the PACU on the completion of their surgery,

Figure 1. OR suite. OR, operating room; PACU, postanesthesia care unit; ICU, intensive care unit; MC, medium care; CCU, coronary care unit.

although critical inpatients (eg, cardiac or thoracic) are admitted to one of the other postoperative units because of specialized resource requirements and a genuinely higher demand for care.

Furthermore, the model should account for the following characteristics. A surgical case is nonpreemptive, indicating that the process cannot be interrupted in each of the two hospitalization stages. In addition, once a surgery is started, the two processing steps corresponding to the intraoperative and postoperative stages should be performed consecutively, without waiting times between them.²³

The flow shop-scheduling problem, introduced in the previous paragraph, can be formally modeled as a MILP model. The primary objective of the MILP is to determine the sequence and starting times for a selection of OR cases on their admission date, such that the overall cost incurred is minimized. It is assumed that elective and nonelective urgent patients have already received a hospitalization date. Moreover, the model aims to find the surgery sequence and corresponding PACU nursing staff level, with the best tradeoff between expected costs for OR overtime and nursing staff salary expenses in the PACU. OR overtime is defined as the period each OR is open past a defined end time (eg, 17:00). By minimizing postoperative labor costs, we strived to level the variability in inflow of patients to the PACU, which in turn should result in a decrease of variability in bed demand and smoothen the workload for the staff personnel.

Formal Notation

The formal parameter notation for the two-stage flexible flow shop problem is given as follows. Denote by K the set of surgical cases (k), categorized into uniform patient groups, and which are hospitalized on day d . The defined uniform patient categories from Table 2 are used for categorization, which is required to reduce the number of decision variables for the algorithm. Modeling assumptions allow the algorithm to sequence elective and nonelective urgent surgical cases on their admission date. The model will therefore comprise a finite time horizon of one workday with length T_{id} , which is discretized into uniform time intervals ($t \in T$) of x minutes.

Indices i , with $i \in I$, denotes the hospitalization stage. Each patient k has to pass through the two stages (eg, intraoperative and postoperative stages), respectively, although the postoperative hospital unit where the patient can recover from the

residual effects of anesthesia is dependent on the patient type. The set $K^r \subseteq K$ denotes the set of surgical cases containing PACU ($r = 1$) or ICU, MC, ward, PACU (intensive care), and CCU ($r = 2$) patients, where r , with $r \in R$, indicates the postoperative classification indices. Please note that the defined flow shop problem only accounts for the postoperative stay in the PACU ($r = 1$); critical inpatients, admitted to one of the other postoperative units, will not be included in the defined flexible two-stage flow shop problem. Moreover, indices j , with $j \in J$, indicates the resource type used to treat a patient during a certain time interval t . Depending on the stage classification indices i , indices j refers to a specific OR or hospital bed in the PACU. Given the fact that certain surgical procedures can only be performed in dedicated ORs because of specialized resource requirements, the set $K^j \subseteq K$ is introduced, indicating the selection of patients (k) assigned to OR j on day d . All other resources necessary for anesthetic and surgical procedures are assumed to be available.

The two-stage flexible flow shop problem comprises three types of decision variables. The binary variable X_{kijt} indicates the arrival time for patient k , at stage i on resource j . The period that patient k occupies resource i, j is given by the variable, Y_{kijt} , and the length of the period is determined based on either the total surgery duration ($i = 1$) or LOS ($i = 2$) in the PACU. Both the total surgery duration and LOS are assumed to be deterministic, dependent on the patient type, and are represented by the variables O_k and L_k , respectively. The total surgery duration and LOS in the PACU for each patient type, represented by the (rounded) average from Table 2, are discretized into uniform intervals with length x . Moreover, it is assumed that turnover times, including cleaning and set-up times, are included in the generated total surgery durations. This is because the obtained data set did not contain any explicit recordings regarding the aforementioned subject. Last, transfer times from the hospital ward to the OR, or from the OR to the PACU, are not taken into account, indicating that the arrival time of the patient at the PACU equals the completion time of the surgery. The transfer times from the holding to the ORs are therefore negligible and rarely contribute to overused OR time.

The second included decision variable relates to the postoperative labor cost objective. The binary variable α_{lpt} indicates the start time of the work shift for a PACU nurse p , with T_{ls} indicating the length of the workday. Modeling assumptions allow the algorithm to start a new work shift on every time interval t , with the restriction that one PACU nurse is allowed to work only one work shift per day d . Moreover, the length of the work shift T_{ls} may vary between the PACU workforce, with the default values corresponding to an 8 hour ($T_{ls} = 1$; 1 full-time equivalent) and 4 hour ($T_{ls} = 2$; 0.5 full-time equivalent) workday. The binary variable β_{pt} indicates whether nurse p works at the concerning time interval. The minimum number of nurses required in each time interval (eg, $Neednurses_t$) (Equation 14) is dependent on the number of occupied hospital beds and the patient acuity level W_{kt} , which provides a measure for the number of nurse equivalents required to care safely for each patient. This value is subsequently corrected for a nurse capacity safety margin of about 20% to cover up for any unanticipated change in demand for care and to satisfy some predefined ergonomic constraints throughout the planning period. Gunawan and Lau²⁴ suggested that a safety margin of about 20% of the total resource requirement will be sufficient. Emergency cases are included as the deterministic fraction of additional required capacity per time interval at the PACU, caused by the outflow of patients from the emergency OR. Emergency classified patients are unpredictable, indicating that they cannot be included as a target throughput for any given planning period. However, because most of these cases will be performed in a dedicated emergency OR, any increase in nurse workload in the PACU caused by the outflow of

Table 2
Uniform Patient Categories

No.	Patient Category					Surgery Duration				LOS			
		Description	Priority	ASA	Acuity	Planned Duration	N	μ	Estimate σ	Estimate CV	μ	Estimate σ	Estimate CV
1	Normal healthy patient	E, O	1	None (1:2)	$x \leq 60$	1,263	51,212	3,875	18,076	0,343	0,352	60,334	4,027
2	Normal healthy patient	S	1	None (1:2)	$x \leq 60$	139	56,989	3,943	26,4816	0,443	0,464	63,162	4,069
3	Normal healthy patient	E, O	1	None (1:2)	$60 < x \leq 120$	1,009	92,283	4,468	32,026	0,337	0,379	75,219	4,250
4	Normal healthy patient	S	1	None (1:2)	$x > 60$	79	86,321	4,383	34,6952	0,387	0,436	72,528	4,205
5	Normal healthy patient	E, O	1	None (1:2)	$120 < x \leq 210$	368	157,131	5,016	46,155	0,288	0,290	92,898	4,473
6	Normal healthy patient	E, O	1	None (1:2)	$x > 210$	81	246,821	5,440	95,034	0,371	0,366	104,467	4,578
7	Mild systematic disease	E, O	2	Mild (1:2)	$x \leq 60$	2,117	55,140	3,954	18,983	0,335	0,344	71,4	4,198
8	Mild systematic disease	S	2	Mild (1:2)	$x \leq 60$	124	57,867	3,955	27,756	0,455	0,508	73,836	4,223
9	Mild systematic disease	E, O	2	Mild (1:2)	$60 < x \leq 120$	2,528	92,934	4,482	30,151	0,316	0,323	82,083	4,344
10	Mild systematic disease	S	2	Mild (1:2)	$x > 60$	108	100,766	4,511	48,008	0,452	0,468	76,955	4,260
11	Mild systematic disease	E, O	2	Mild (1:2)	$120 < x \leq 210$	908	158,521	5,025	46,1377	0,285	0,294	101,93	4,546
12	Mild systematic disease	E, O	2	Mild (1:2)	$x > 210$	249	270,363	5,539	97,100	0,348	0,359	118,707	4,679
13	Severe systematic disease	E, O	3	Moderate (1:1)	$x \leq 60$	571	55,775	3,967	18,905	0,330	0,342	75,337	4,243
14	Severe systematic disease	S	3	Moderate (1:1)	$x \leq 60$	52	56,5004	3,948	24,5027	0,415	0,423	79,325	4,294
15	Severe systematic disease	E, O	3	Moderate (1:1)	$60 < x \leq 120$	723	94,777	4,492	33,783	0,346	0,368	90,943	4,415
16	Severe systematic disease	S	3	Moderate (1:1)	$x > 60$	71	108,976	4,621	42,2667	0,374	0,406	96,916	4,489
17	Severe systematic disease	E, O	3	Moderate (1:1)	$120 < x \leq 210$	327	163,343	5,046	52,9334	0,316	0,315	111,42	4,566
18	Severe systematic disease	E, O	3	Moderate (1:1)	$x > 210$	70	239,431	5,444	63,463	0,261	0,262	115,846	4,397
19	Severe systematic disease, constant threat to life	E, O	4	Substantial (2:1)	$x \leq 90$	35	61,338	4,008	30,241	0,466	0,491	70,050	4,089
20	Severe systematic disease, constant threat to life	S	4	Substantial (2:1)		11	90,352	4,409	41,183	0,434	0,445	89,337	4,369
21	Severe systematic disease, constant threat to life	E, O	4	Substantial (2:1)	$x > 90$	30	188,728	5,078	116,823	0,469	0,553	84,723	4,320
22	Unknown ASA condition	E, O	5	Unknown (1:2)	$x \leq 60$	132	39,8269	3,519	24,9348	0,575	0,543	48,847	3,765
23	Unknown ASA condition	S	5	Unknown (1:2)	$x \leq 60$	392	58,6236	3,954	30,1339	0,484	0,588	66,885	4,086
24	Unknown ASA condition	E, O	5	Unknown (1:2)	$60 < x \leq 120$	50	91,9679	4,427	41,8947	0,434	0,445	71,191	4,081
25	Unknown ASA condition	S	5	Unknown (1:2)	$x > 60$	191	93,3705	4,442	42,6149	0,435	0,431	87,961	4,362
26	Unknown ASA condition	E, O	5	Unknown (1:2)	$x > 120$	34	149,834	4,911	70,041	0,445	0,525	66,269	4,013

LOS, length of stay; ASA, American Society of Anesthesiologists; CV, coefficient of variation; E, elective case; O, unknown whether case is elective or emergency; S, emergency.

these patients can be considered independently from the obtained scheduling solution. The portion of nondeterministic emergent demand that cannot be fulfilled using the dedicated emergency OR was omitted throughout the course of this study.

The third and last decision variable is introduced to preserve some predefined ergonomic constraints. The binary variable γ_{lpt} indicates the start time of the lunch break for a PACU nurse p , with a length b of 30 minutes. Modeling assumptions allow the algorithm to start a lunch break on every time interval t within the period between 11.30 and 13.30 hours, with the restriction that each PACU nurse is entitled to one lunch break per day d . Moreover, the binary variable δ_{lpt} indicates whether nurse p has a lunch break at the concerning period. Bed capacity in postoperative departments is respected with the introduction of an upper-bound value Q_{rt} . Overutilization of the ORs in terms of overtime is penalized with cost CO_j per time interval t , whereas violating permitted opening time of postoperative departments is penalized through increased labor costs CS_{rt} for working beyond regular opening hours. By finding the best tradeoff between postoperative labor costs and expected costs for OR overtime, we strive to reduce the variability

in inflow of patients to the PACU, which in turn should result in less variability in bed demand and peaks in workload for the nursing staff (Table 3).

MILP Model

An MILP formulation for the two-stage flexible flow shop problem is shown in Table 4.

In the aforementioned formulation, the objective function (1) aims to minimize the expected costs for OR overtime and nursing staff salary expenses in the PACU. Constraint (2) imposes the restriction that for any resource j at stage i , at most one patient can be admitted at the beginning of each time interval t . Constraint (3) implies that when a patient occupies a certain resource j at stage i , no other treatment can start at the same resource until this treatment is finished. Constraints (4) and (8) denote the relationship between the assignment variables X_{kijt} and Y_{kijt} . Constraint (5) defines the precedence relationship between the two hospitalization stages and ensures that a patient is transferred to the PACU on the completion of their surgical intervention. Constraints (6) and

Table 3
Overview of Indices, Parameters, and Decision Variables

Indices	
<ul style="list-style-type: none"> k: Patient indices i: Stage indices t: Time indices; discrete time intervals of x minutes p: PACU nurse indices l: PACU nurse workshift indices j: Resource indices r: Postoperative classification indices K^d: Selection of inpatient admissions assigned to ORj on day d K^r: Selection of inpatient admissions assigned to a bed at postoperative facility r on day d 	$k \in \{1, 2, \dots, N\}$ $i \in \begin{cases} 1 & \text{Intraoperative period} \\ 2 & \text{Postoperative period} \end{cases}$ $t \in \{1, 2, \dots, T\}$ $p \in \{1, 2, \dots, S\}$ $l \in \begin{cases} 1 & \text{Workshift with length } T_{1s} \\ 2 & \text{Workshift with length } T_{2s} \end{cases}$ $j \in \{1, 2, \dots, M\}$ $r \in \begin{cases} 1 & \text{PACU} \\ 2 & \text{ICU, MC, CCU, PACU (IC), Ward} \end{cases}$ $K^j \subseteq K$ $K^r \subseteq K$
Parameters	
<ul style="list-style-type: none"> a: PACU nurse capacity safety margin b: Length of PACU lunch break THR$_j$: target patient throughput at resource j O_k: Gross surgery duration of patient k L_k: LOS PACU of patient k W_{kt}: Patient acuity for patient k at time interval t Q_{rt}: Bed capacity at postoperative facility r on time interval t T_{id}: Duration of workday at stage i T_{is}: Duration of type 1 PACU workshift CS$_{rt}$: Salary expenses of nursing staff in postoperative facility r on time interval t CO$_t$: Overtime cost per time interval t of operating room j Emergency$_t$: Average demand for care emergency OR in time interval t 	$\text{Emergency}_t \in \begin{cases} 0 & t < 13.00 \\ 0.5 & 13 : 00 \leq t \leq 19 : 00 \end{cases}$
Decision variables	
<ul style="list-style-type: none"> X_{kijt}: Decision variable; binary variable, value indicates 1 if patient k arrives at resource i, j on time interval t Y_{kijt}: Binary variable; value indicates 1 if patient k occupies resource i, j on time interval t α_{pt}: Decision variable; binary variable, values indicates 1 if nurse p starts his/her work shift on time interval t β_{pt}: Binary variable, value indicates 1 if nurse p works during time interval t γ_{pt}: Decision variable; binary variable, value indicates 1 if nurse p starts his/her lunch break on time interval t δ_{pt}: Binary variable, value indicates 1 if nurse p has a lunch break on time interval t 	

(7) prevent the model from including critical inpatients, with an outflow to either the ICU, MC, CCU, general ward, or PACU (intensive care), in the intraoperative and postoperative hospitalization stage. Constraint (9) implies that all patients who are assigned to a certain admission date d are required to undergo their surgery on the same day. Constraint (10) ensures the respect of postoperative bed capacity through the introduction of an upper-bound value Q_{rt} . Constraint (11) indicates the start time of the lunch break for a PACU nurse, with the restriction that each PACU nurse is entitled to only one lunch break per day d (constraints 12 and 13). Constraint (14) determines the demand for nurse care in a certain time interval, where constraint (25) prohibits this value becoming nonnegative. Constraint (15) prohibits that one PACU nurse p works more than one work shift per day d . Constraint (16) indicates the relationship between the assignment variables α_{pt} and β_{pt} . Constraint (17) implies that the number of scheduled nurses during each time interval t should be sufficient to cover the demand for nursing care. Constraint (18) determines the expected OR overtime, where constraint (26) prohibits this variable from becoming nonnegative. Constraints (19), (20), (21), (22), (23), and (24) ensure the integrality of the assignment variables.

Sensitivity Analysis on Model Input Parameters

The MILP formulation for the defined flow shop problem is written in Matlab R2014b (The MathWorks, Inc, Benelux) and is subsequently linked with the ILOG CPLEX 12.7.1 optimization library using the CPLEX connector (IBM, Armonk, NY). All computational experiments were executed on a 2 GHz Intel Core i7 PC with 16 GB RAM and Windows 7 Home Premium and were truncated after 300 seconds of running time. The computation time is

limited as the operating room coordinator (ORC) often wants to compare multiple surgery schedules and change the settings of the problem accordingly.^{25,26}

We performed a sensitivity analysis to assess the robustness of the defined MILP model. The model input parameters included in Table 5 were given as input constraints by the hospital and are therefore considered to be fixed. Other input parameters, including the length (x) of each uniform time interval, and an upper bound to the number of PACU nurses that the algorithm is allowed to roster, are to be decided by the authors and will therefore form the basis for the sensitivity analysis. The level of variation of the included parameters is displayed in Table 6, although the choice of the parameter variation is limited by computing power or integer feasibility. The sensitivity analysis is performed by varying every parameter to the low and high values, whereas keeping the values for the remaining parameters at the middle value. The default setting of all parameters with the mid value resulted in the best tradeoff between the quality of the obtained solution and computational requirements.

MILP Model Parameter Tuning

We modified the default values of some CPLEX-based parameters to upgrade the performance of the defined MILP and to speed up computation time. Although the ILOG CPLEX 12.7.1 optimization library usually found a (near) optimal solution within the calculation time window of 300 seconds, the returning Exitflag value most often indicated that the search algorithm potentially terminated on a local minimum, as the first order optimality measure was above the function tolerance. Moreover, the running log displayed that the algorithm quickly found a solution within a five percent

Table 4
An MILP Formulation for the Two-Stage Flexible Flow Shop Problem

◦ Objective function		
• $Z = \min \left[\left(\sum_{j \in J} \text{Overtime}_j * \text{CO}_j \right) + \left(\sum_{l \in L} \sum_{p \in P} \sum_{t \in T} \beta_{lpt} * \text{CS}_{rt} \right) \right]$		(1)
◦ Subject to		
• $\sum_{k \in K} X_{kijt} \leq 1$	$\forall i \in I, j \in J, t \in T$	(2)
• $\sum_{k \in K} Y_{kijt} \leq 1$	$\forall i \in I, j \in J, t \in T$	(3)
• $Y_{k1jt} = \sum_{t=O_k+1}^t X_{k1jt}$	$\forall k \in K^I, i \in I, j \in J$	(4)
• $X_{k2jt} = X_{k1jt-O_k+1}$	$\forall k \in K^r, i \in I, j \in J, t \in T$ $r < 2$	(5)
• $X_{k1jt} = 0$	$\forall k \in K^r, i \in I, j \in J, t \in T$ $r > 1$	(6)
• $X_{k2jt} = 0$	$\forall k \in K^r, i \in I, j \in J, t \in T$ $r > 1$	(7)
• $Y_{k2jt} = \sum_{t=L_k+1}^t X_{k2jt}$	$\forall k \in K^r, i \in I, j \in J$ $r < 2$	(8)
• $\sum_{k \in K^I} \sum_{t \in T} X_{kijt} = \text{THR}_j$	$\forall j \in J, i \in I$ $i < 2$	(9)
• $\sum_{k \in K^r} \sum_{j \in J} Y_{kijt} \leq Q_{rt}$	$\forall i \in I, t \in T, r \in R$ $i > 1, r < 2$	(10)
• $\delta_{lpt} = \sum_{t=b+1}^t \gamma_{lpt}$	$\forall p \in P, l \in L$	(11)
• $\sum_{p \in P} \sum_{l \in L} \gamma_{lpt} = 1$	$\forall t \in T$ $l < 2$	(12)
• $\gamma_{lpt} = 0$	$\forall p \in P, l \in L, t \in T$ $14 \leq t \leq 22$	(13)
• $\text{Neednurses}_t = \left[a * \sum_{k \in K^r} \sum_{j \in J} W_{kt} * Y_{kijt} \right] \text{Emergency}_t$	$\forall i \in I, t \in T, r \in R$ $i > 1, r < 2$	(14)
• $\sum_{l \in L} \sum_{t \in T} \alpha_{lpt} \leq 1$	$\forall p \in P$	(15)
• $\beta_{lpt} = \sum_{t=T_k+1}^t \alpha_{lpt}$	$\forall p \in P, l \in L$	(16)
• $\sum_{p \in P} \sum_{l \in L} (\beta_{lpt} - \gamma_{lpt}) \geq \max[\text{Neednurses}_t]$	$t \in T$	(17)
• $\text{Overtime}_j = \sum_{k \in K^I} \sum_{t=T_d}^T Y_{kijt}$	$\forall i \in I, j \in J$ $i < 2$	(18)
• $X_{kijt} \in \{0, 1\}$	$\forall k \in K_j, i \in I, j \in J, t \in T$	(19)
• $Y_{kijt} \in \{0, 1\}$	$\forall k \in K_j, i \in I, j \in J, t \in T$	(20)
• $\alpha_{lpt} \in \{0, 1\}$	$\forall p \in P, t \in T, l \in L$	(21)
• $\beta_{lpt} \in \{0, 1\}$	$\forall p \in P, t \in T, l \in L$	(22)
• $\gamma_{lpt} \in \{0, 1\}$	$\forall p \in P, t \in T, l \in L$	(23)
• $\delta_{lpt} \in \{0, 1\}$	$\forall p \in P, t \in T, l \in L$	(24)
• $\text{Neednurses}_t \geq 0$	$\forall t \in T$	(25)
• $\text{Overtime}_j \geq 0$	$\forall j \in J$	(26)

difference with respect to a hypothesized best integer objective, although it kept iterating with no improvement in the objective function. To prevent the algorithm from making continuous iterations without obtaining an improvement, the authors decided to increase the MIP gap tolerance to 0.05. This new option structure forces the algorithm to truncate optimization either after 300 seconds of running time or when the feasible scheduling solution falls within the aforementioned tolerance gap.

Retrospective Study

An ex post facto computation experiment was designed and performed, in conjunction with discrete-event simulation, to validate the defined flow shop scheduling algorithm and assess its rescheduling impact. Discrete-event simulation was chosen to highlight the dynamic functioning of the surgical suite.²⁷

Historical admission profiles from the year 2016 were used as production targets, with the functioning of the algorithm being repeatedly assessed for various configurations of OR case lists under artificial environmental conditions. The AS-IS situation was also replicated using the same case list configurations with equal (stochastic) surgery durations and LOS distributions. The study can therefore be considered as a longitudinal study with a limited time

frame. The obtained stochastic simulation results (eg, 80 percentile) were used as input for the algorithm to reconsider the initial nurse roster design obtained under the deterministic situation. The simulation results were obtained from 100 independent simulation runs per OR case list configuration, with one workday replicated per simulation run. The historical case mixes of 04.01.2016, 10.03.2016, and 08.04.2016 were used as test instances, although for readability, only the results obtained for the first case mix will be visualized in the results section of this article.

Table 5
Model Input Parameter Values (Fixed)

Variable Name	Notation	Value
Bed capacity at level 1 PACU	Q_{rt}	15
Number of available ORs	J	18
Regular working hours ORs	T_{1d}	8:00–17:00 h (9 h)
Regular working hours PACU	T_{2d}	8:00–20:00 h (12 h)
Planning horizon surgical suite	T	8:00–21:00 h (13 h)
Duration of PACU work shift (1 FTE)	T_{1s}	9 h
Duration of PACU work shift (0.5 FTE)	T_{2s}	4 h
Salary expenses nursing staff	CS_{rt}	€35.02 per h
Salary expenses nursing staff overtime	CS_{rt}	€70.04 per h
OR overtime labor costs	CO_j	€674.25 per h

PACU, postanesthesia care unit; ORs, operating rooms; FTE, full-time equivalent.

Table 6
Sensitivity Analysis on Model Input Parameter Values

Variable Name	Notation	Low Value	Middle Value	High Value
Length uniform time interval	X	12 min	15 min	20 min
PACU nursing staff (1 FTE)	P_1	6	8	10
PACU nursing staff (0.5 FTE)	P_2	0	2	4

PACU, postanesthesia care unit; FTE, full-time equivalent.

The simulation of the function of the surgical suite includes three stages. The first stage (I) comprises the derivation of an OT case list for each OR. The second stage (II) comprises the simulated execution of the surgical cases on their admission date. In stage three (III), the workday for the PACU nurses is simulated.

Stage I: Derivation of OT Case Lists

The first simulation stage comprises the (I) derivation of an OT case list for each OR. The relative position and starting time of each surgical treatment in the OT case list is either determined by the obtained MILP solution or derived from the original surgery schedule made by the ORC. By convention, in the second stage (II), each patient was given a fixed acuity level (Table 2). It is assumed that transitions from one acuity level to another are not possible throughout the patient's stay in the PACU.

Stage II: Simulation of Patient Flow

The second stage comprises simulating the flow of patients through the two consecutive hospitalization stages in the surgical suite. (I) For each OR, the generated OT case list is first sorted according to each case's relative position in the permutation sequence and expected starting time. (II) Moreover, total surgery durations and LOS in the PACU are generated for each case from a lognormally distributed random variable, with a mean and standard deviation depending on the patient type (Table 2). In case a negative value was returned, this second step was iterated until a nonnegative value was obtained. (III) When an OR is available for a new case at the beginning of the shift, the first case from the OT case list is started at the exact moment in time specific by the MILP obtained solution. In case of replicating the AS-IS situation, the starting times as defined by the ORC are used. (IV) On the completion of the surgery, the patient is discharged immediately to the PACU. It was decided to consider a hypothetical unlimited nurse capacity in the PACU, such that the patient flow from the ORs to the PACU was unaffected by the available nurse capacity. In the current situation, solely the bed capacity is leading in the decision to postpone an admission to the PACU. Once a surgery is completed and the patient is discharged, a subsequent treatment in the permutation schedule is able to start for the concerning OR. Please note that although the expected starting times (obtained under a complete deterministic situation) was maintained as much as possible during the simulation, this requirement is offset under the condition that the starting time for surgery j is smaller than the completion time for surgery i , where surgery i is the predecessor of j in the permutation schedule. Under these conditions, the starting time for surgery j equals the completion time of surgery i . (V) The simulation process with respect to the patient flow terminates when the treatment in the PACU is completed and the patient is discharged to the general ward.

Stage II: Simulation of Work Shifts PACU Nurses

The third and final simulation stages comprised the replication of the work shifts for the rostered PACU nurses. For the simulation of the TO-BE situation, the starting times and number of both full-time and part-time work shifts are defined under a complete deterministic situation, with respectively an 8 hour or 4 hour

duration. For the simulation of the AS-IS situation, a total of eight full-time nurses are rostered, with the starting times of the shifts ranging between 07:30 and 12:30. The starting times for the lunch breaks are chosen such that the overlap between two consecutive breaks is minimized.

Results

Patient Categorization and Distribution Fitting

The obtained data sample of 14,295 individual cases was first partitioned into 26 uniform patient categories to reduce the number of decision variables for the scheduling algorithm and increase the applicability of the proposed model for numerous health care institutions. On using the identified patient categories as input, probability distribution fitting analysis indicated that a lognormal distribution is best suited to approximate the procedure times and LOS for each patient group. These propositions were confirmed by a one-sample Kolmogorov-Smirnov test. The identified patient categories with their distribution parameters (ie, mean, standard deviation) are included in Table 2.

Computational Results Flow Shop Algorithm

The MILP determined OR scheduling solution is visually represented in Figure 2A. For readability, only the sequencing results for one particular OR (eg, OR 12) will be visualized in the results section of this article.

Regarding Figure 2A, the blue colored time intervals represent the occupation of the OR by a particular patient, with the first occupied interval indicating the starting time of the intraoperative hospitalization stage. Remark that the nonpreemptive scheduling requirement is satisfied by the obtained solution, as no surgery is interrupted. Moreover, the precedence relationship between two consecutive treatments is respected because of the fact that no treatment is expected to start before the previous one is finished. Third and last, the two processing steps (eg, intraoperative and postoperative stage) were performed consecutively without waiting times between them, indicating that the patient is expected to arrive in the PACU on the completion of their surgery treatment (Figure 2B).

In addition to the resequencing solution, the flow shop algorithm provided an appropriate PACU workforce roster for the upcoming planning period. Regarding Figure 2C, it appeared to be optimal to roster six full-time and one part-time PACU nurse under the MILP determined surgery sequence, with the blue colored time intervals representing the duration of the work shifts. The blank gaps represent the lunch breaks for the staff personnel.

Figure 3 displays the expected demand for nurse care per time interval in the PACU, which is offset against the nurse capacity made available by the scheduling algorithm. This figure shows a fairly stable expected nurse demand throughout the day, with no capacity shortages occurring under a complete deterministic situation.

Figure 2. Computational results mixed integer linear programming—operating room 12 (Panel A: Surgery schedule; Panel B: PACU schedule; and Panel C: PACU nurse schedule). PACU, postanesthesia care unit.

Figure 3. Computational results mixed integer linear programming (expected workload vs nurse capacity postanesthesia care unit).

Figure 4. Simulation results—Panel A: Bed occupancy PACU; Panel B: Demand for PACU care. PACU, postanesthesia care unit.

Retrospective Results

Bed Occupancy

Figure 4A displays the average evolution of the bed occupancy in the PACU within the given planning horizon. The top part of the figure represents the replication of the AS-IS situation, which is offset against the TO-BE situation under the MILP determined sequence. Both situations display an inevitable increase in bed occupancy in the PACU within the period between 8.00 till 9.40 hours, which is considered to be the warm-up period. Regarding the AS-IS situation (eg, top figure), two additional peaks in bed occupancy can be identified, corresponding to regularly observed behavior in the PACU. The latter admission peak is caused by the closing of the ORs. After time, the average number of patients staying at the PACU gradually diminishes.

Replicating the TO-BE situation (eg, bottom figure) resulted in a more stable bed occupancy throughout the given planning horizon. The slight drop in bed occupancy in the early afternoon is presumably the result of the algorithm anticipating the lunch breaks for the staff personnel. The average bed occupancy rate, expressed as the average number of occupied beds divided by the available bed capacity, was around 30% in both situations.

Demand for Care

Figure 4A displays the average demand for nurse care in the PACU. When one compares this result with the results from the previous paragraph, it can be remarked that correcting the average bed occupancy in the PACU with the acuity level does not significantly affect the shapes of the curves; it only results in a vertical translation. Figure 4B displays, besides the average demand for care, also the upper 75 and 95 percentile.

Workload Staff Personnel

The average labor demand in the PACU is offset in Figure 5 against the nurse capacity as made available in either the AS-IS (eg, top figure) or TO-BE situation (eg, bottom figure). When considering the AS-IS situation, it became clear that some periods could be identified with a nurse capacity shortage, despite the significant amount of nurses scheduled. Replicating the TO-BE situation resulted in a significantly smaller PACU workforce, yet no capacity shortages could be observed.

Other Performance Measures

Last, the two replicated situations were compared on the basis of three additional performance measures that are regularly applied in the current literature (eg, PACU completion time, PACU overtime, OR overtime). By applying the flow shop scheduling algorithm, the PACU completion time can on average be reduced by 25 minutes as compared with the AS-IS situation. Moreover, simulation results show that the amount of overtime hours in the PACU and the OR can on average be reduced by 22 minutes, respectively, 2 hours when one adheres to the MILP determined schedule.

Practical Scheduling Guidelines

Based on our findings, we can derive practical scheduling guidelines, which may help to smooth the PACU workload as presented in this study (Table 7).

Discussion

In this study, an integrated ORs' scheduling methodology was developed that determines the sequence for a given OR case list configuration and concerning nursing staff level, with the objective

Figure 5. Simulation results—expected workload versus nurse capacity postanesthesia care unit (top: AS-IS situation; bottom: TO-BE situation).

Table 7
Scheduling Guideline

Before 11 a.m.: ASA 3 and scheduled OR duration >60 min
After 2 p.m.: ASA 3 and scheduled OR duration <60 min
After 11 a.m. and before 4 p.m.: ASA 1, 2, 3 and scheduled OR duration <60 min
Before 11 a.m.: ASA 1, 2, 3 and scheduled OR duration >210 min
Other surgeries: alternate short and long expected OR durations

ASA, American Society of Anesthesiologists; OR, operating room.

to level the inflow of patients to the PACU. Based on the obtained simulation results, it can be concluded that prospectively sequencing OR cases in view of the outflow of patients to the PACU can effectively decrease the variability in bed demand and smooth the workload for the staff personnel. Moreover, simulation results indicate that applying the algorithm leads on average to a decrease in PACU completion time and less overtime hours for the surgical suite.

In the present study, we used the conceptual flow shop scheduling approach as introduced by Heydari and Soudi¹⁴ as a reference guide, although we adjusted the model with the introduction of a nurse roster component and the usage of a different objective function and time representation. Their initial usage of a makespan objective would have most likely involved dense surgery schedules, which in turn lead to peaks in bed demand and workload for the staff personnel. Our findings are in line with previous studies that acknowledged the importance of an integrated OR planning methodology. However, this study seems to further extend the work in this field,^{6,7} which only included the available resources for the PACU, ICU, or ward as a downstream capacity constraint and therefore mainly focused on improving OR efficiency. Our proposed planning methodology sequenced OR cases in view of the outflow of patients to postoperative departments,¹⁴ and while doing so, tried to optimize the global performance of the surgical suite. This change in perspective may provide important insights in potential methods to level OR outflow to postoperative departments and may lead to a better understanding of how to match the demand for care to staffing at downstream departments. Last, this study can be considered as an extension to prior research¹ as we aimed to sequence multiple OR cases simultaneously 1 or 2 days before the actual surgery date.

The derived planning methodology, however, is likely to face some challenges during implementation. The foremost challenge can be described as the disruption of routine behavior. The stability in the working atmosphere as the result of a fairly standard session roster is no longer guaranteed when using the algorithm. Resequencing decisions will be made regardless of the availability of the medical specialists and dedicated resource requirements. As a consequence, the derived OR planning should become leading in the specialist's decision of when to preserve time for secondary activities, including the provisioning of medical consults.

Limitations

Our study has some limitations that need to be kept in mind during the interpretation of the results. The first limitation relates to the research delineation used to formulate the model. The research objective was focused toward deriving OR schedules in view of the patient flow to the PACU. However, because there also exist an outflow of patients to other postoperative departments, the derived OR schedule may not be realistic or it may affect the performance of other postoperative departments. Incorporating multiple downstream departments in the decision process will greatly increase the computational effort required to solve the problem, and it is questionable whether an actual (Pareto) optimal solution can be obtained. Still, an interesting suggestion for further research

would be to investigate whether the derived planning methodology could also be adapted and applied to other postoperative departments, like the ICU.

A second limitation relates to the time representation used to formulate the model. We opted to use a discrete-time approach, in which the time horizon of interest is divided into uniform time intervals. The disadvantage of this approach is that it is essentially an approximation of time, and every activity that affects the surgery schedule can only take place at a specific instance of each time interval. A suggestion for further research would be to adopt a continuous-time approach for the defined flow shop scheduling algorithm.

The third limitation relates to the concept of uncertainty. The derived flow shop algorithm provides an optimal OR sequence under a complete deterministic situation, although the derived sequence is a heuristic solution when applied in a real (stochastic) hospital environment. The nurse roster redesign is determined based on the stochastic simulation results (eg, 80 percentile), indicating that any uncertainty in surgery durations and LOS distributions is taken into account. The derived OR sequence is, however, determined under a complete deterministic situation and therefore lacks these randomized components. Here lies a possibility for future work.

When introducing the model in other hospitals, constraints on availability of professional staff and heterogeneity of room equipment might also be a limitation. Therefore, to increase the practical applicability of the model, a suggestion for future work could be to include the availability of medical specialists during the day. A limited availability of medical specialists may, however, constrain the quality of the provided scheduling solutions. Last, the proposed planning methodology is solely validated and assessed in an artificial environment using retrospective simulation. Further research is required to prospectively evaluate the presented findings in this study.

Conclusion

Our simulation results confirmed the hypothesis that prospectively sequencing OR cases can effectively decrease the variability in bed demand and smoothen the workload for the staff personnel at the PACU. Moreover, applying the algorithm leads to a decrease in PACU completion time and a reduced amount of overtime hours for the surgical suite. As such, an integrated OR planning methodology facilitates hospitals in improving OR efficiency.

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