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IMPROVING QUALITY OF CARE IN A MULTIDISCIPLINARY EMERGENCY DEPARTMENT BY THE USE OF SIMULATION OPTIMIZATION: PRELIMINARY RESULTS

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ABSTRACT

A major challenge of an emergency department (ED) is managing the growing patient volume without diminishing quality of care nor increasing costs. Therefore, this case study aims at minimizing the average patient's length-of-stay (LOS) subject to a given staffing budget. It is based on data of a multidisciplinary ED in Germany with an annual volume of 50,000 patients. We analyze the impact of process modifications, staff pooling, and optimized staffing levels on the LOS. In order to optimize staffing levels, we combine optimization models with discrete-event simulation. The simulation model is built on treatment processes of different medical specialties that were mapped by time-motion studies. Results show that avoiding boarding time and pooling of nurses originally assigned to internal medicine or neurology are particularly promising. These lead to improvements of 15% and 14% in avg. LOS, respectively. Optimizing staff allocation results in reductions of up to 9% in avg. LOS.

1 INTRODUCTION

Emergency department (ED) crowding is a worldwide challenge (Pines et al. 2011). It adversely affects quality of care, patient safety, and employee satisfaction (Hall 2006). The magnitude of ED crowding can be measured by the quality metrics LOS, the patient's door-to-doctor-time (DTD), and the 4-hour-standard. This standard states that 95% of the patients stay less than four hours within the ED (National Quality Forum (NQF) 2009). In order to improve those metrics, healthcare processes have to be well-designed and resource capacity has to match the ever increasing demand (Hall 2006; Rademakers et al. 2011). In Germany, the ED patient census exhibits an annual increase of 4-8% over the last ten years (Riessen et al. 2015) while the capacity of the ED system has not kept pace. This situation results in a widening gap between the quality of emergency care expected and received by patients (Institute of Medicine 2007). On the one hand, tight budgets limit the allocation of resources. But on the other hand, it has been realized that better quality of care often goes hand in hand with lower total care costs (Zhang et al. 2015). Based on real-world data of an ED in Germany, this case study quantifies the effects of different process improvements on the previous mentioned quality metrics by using discrete-event simulation (DES). Furthermore, for each of the analyzed scenarios, we aim at finding staffing levels that minimize the avg. LOS subject to a given budget by combining the simulation model with a generic optimization software.

The paper is structured as follows: Section 2 gives a compact overview on literature related to the combination of optimization and simulation. Section 3 describes the ED under study in terms of its layout, the resources used, and the patient arrival patterns. In Section 4, we introduce the optimization model and the DES model. In Section 5, we discuss experimental results. Section 6 describes limitations of our research and gives an outlook on future work.

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2 RELATED LITERATURE

Several authors provide taxonomies and classifications for methods that combine optimization and simulation models (Carson and Maria 1997; Tekin and Sabuncuoglu 2004; Figueira and Almada-Lobo 2014; Juan et al. 2015). Figueira and Almada-Lobo (2014) introduce classification dimensions as, among others, the simulation purpose and the hierarchical structure of the combination. In this study, we leverage the commercial optimization software OptQuest in combination with the simulation software AnyLogic. Glover and Kelly (1996) and Laguna (2011) describe OptQuest in more detail. OptQuest uses the simulation model to evaluate a given solution. This evaluation is used for guiding a metaheuristic called scatter search. According to Figueira and Almada-Lobo (2014), that way of using simulation is called Evaluation Function (EF). Additionally, for the same evaluation purpose, OptQuest constructs an artificial neural network based on historical data points generated by previous simulation runs. Constructing such a surrogate model for solution evaluation is called Surrogate Model Construction (SMC). Further purposes of using simulation in combination with optimization are Solution Generation (SG) and Analytical Model Enhancement (AME). In SG the simulation is used to generate a part of or the whole solution, e.g. it uses a solution calculated by the optimization model as inputs and computes more realistic values by considering stochastic components. AME uses the simulation output to modify an analytical model. For instance, De Bruecker et al. (2015) uses the AME approach to build robust aircraft maintenance personnel rosters that lead to desired service levels. They solve a mixed integer linear programs (MILP) that is iteratively adjusted based on simulation outputs.

Various studies have shown that simulation optimization approaches can be leveraged to improve ED decision making. An overview of those studies is provided by Goienetxea Uriarte et al. (2017). Many of those studies use metaheuristics to search a discrete solution space. Juan et al. (2015) provide a comprehensive review on studies that combine metaheuristics with simulation to solve stochastic combinatorial optimization problems. They argue that generic solvers like OptQuest might not be very efficient compared to more tailored solution methods. Even though, it is used by many authors. E.g., Rico et al. (2007) leverage this software package to propose a nurse allocation policy, which reduces the number of patients waiting in an ED during a pandemic influenza scenario. Weng et al. (2011) use OptQuest to allocate physicians and nurses to areas of an ED in order to maximize the ED performance subject to a maximum staff size. A survey on literature regarding ED simulation applications is provided by Gul and Guneri (2015).

3 EMERGENCY DEPARTMENT SETTING

The University Hospital of Giessen and Marburg at Marburg is an academic hospital with about 1100 inpatient beds. Its ED treats about 50,000 patients per year. The ED comprises 16 medical specialties.

3.1 Layout

The ED area can be divided into different functional sections (Figure 1). The registration and triage area provides first assessment and administrative registration. A waiting area for walk-in patients is integrated in this area. The treatment area comprises resuscitation and exam rooms. In total, there are three resuscitation and twenty exam rooms. The latter are dedicated to different medical specialties. The imaging area accommodates one CT and one X-ray room. A blood gas analysis room is located in the ED as well. The observation unit attached to the ED is spatially separated and not illustrated in Figure 1, because it is not considered in this study.

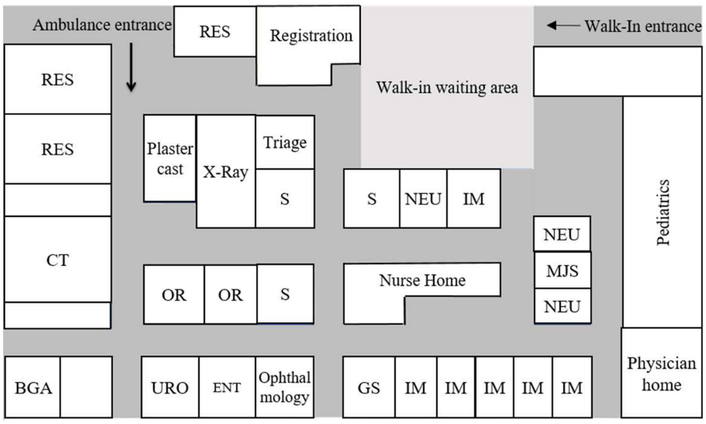

Figure 1: The layout of the ED under study is shown. The following abbreviations are used: IM (internal medicine), NEU (neurology), S (trauma surgery / orthopedics), RES (resuscitation room), BGA (blood gas analysis), OR (operating room), GS (general surgery), ENT (ear-nose-throat), URO (urology).

3.2 Resources

While stationary devices or rooms have been described in the previous section, mobile resources consist of portable devices and staff. Portable devices include an electrocardiogram (ECG) and an ultrasonic device (US). This study considers administrative staff, nurses, and physicians. Staffing is based on given shift schedules. Figure 2 shows the number of available nurses and physicians on weekdays.

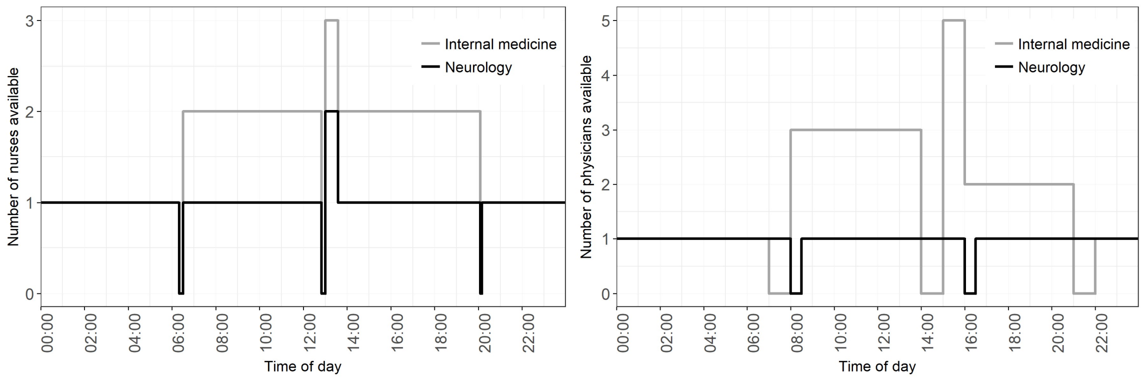

Figure 2: Number of available nurses and physicians according to the current staff setting.

Generally there are three shifts per profession. The beginning and the end of shifts of different professions are not synchronized. Internists are absent three times a day because they have to visit the observation unit. Similarly, there are periods of absence of neurologists and nurses due to shift changeovers. Stationary resources are always available assuming no downtime. Additionally, there are students or interns irregularly present. We have ignored these in this study for reasons of simplicity.

3.3 Patient Arrivals

We chose a simulation horizon of five weeks. The input data regarding patient arrivals is based on real-world data collected from the beginning of May 2016 to the second week of June 2016. Figure 3 exemplary shows the daily patient arrival patterns for six months of 2016. It shows the observed hourly arrival patterns per weekday.

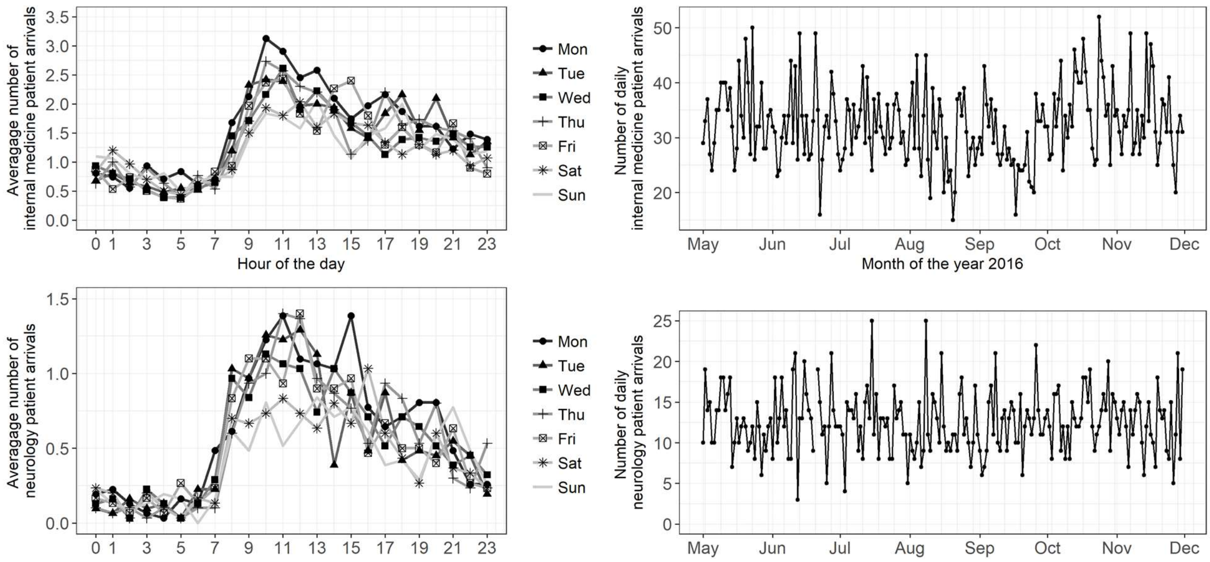

Figure 3: Hourly and daily arrival patterns for internal medicine (IM) and neurology (NEU) patients.

4 SIMULATION OPTIMIZATION

4.1 Optimization Model

The avg. LOS is denoted by $\overline{LOS}$. Parameter B represents the given staffing budget. Let S^r be the set of shifts of staff of type $r \in R$. The integer variable $x_{r,s}$ indicates the amount of assigned staff of type $r \in R$ to shift $s \in S^r$. The maximum amount of assignable staff of type r to shift s is denoted by $J^{r,s}$. $I^{r,s}$ symbolizes the minimum amount of assignable staff of type r to shift s. Wage costs of staff type r for shift s are denoted by $C_{r,s}$. Parameters and variables used in this model are listed in Table 1.

Table 1: Overview of model parameters and decision variables.

		Description	Domain
Parameter	$J^{r,s}$	Max. amount of assignable staff of type r to shift s	$\mathbb{N}_0$
	$I^{r,s}$	Min. amount of assignable staff of type r to shift s	$\mathbb{N}_0$
	R	Set of staff types	{nurse neurology, nurse int. med., neurologist, internist}
	S^r	Set of shifts for staff of type r	see Table 3 in appendix A
Decision variable	$x_{r,s}$	Amount of staff of type r assigned to shift s	$\mathbb{N}_0$

The optimization problem is formulated as follows:

$$\min \quad \overline{LOS} \tag{1}$$
s. t.:
$$\sum_{r\in R} \sum_{s\in S^r} C_{r,s}\, x_{r,s} \leq B \tag{2}$$
$$x_{r,s} \leq J^{r,s} \qquad \forall\, r \in R, \forall\, s \in S^r \tag{3}$$
$$x_{r,s} \geq I^{r,s} \qquad \forall\, r \in R, \forall\, s \in S^r \tag{4}$$

$$x_{r,s} \quad \in \quad \mathbb{N}_0 \qquad\qquad \forall\, r \in R, \forall\, s \in S^r \qquad (5)$$

The objective function (1) aims at minimizing the avg. LOS of all patients in the ED. To this end, the model addresses staff-to-shift-assignment decisions. In order to determine the objective value of a solution, the DES model takes the staff-to-shift-assignment decisions as inputs and outputs the value of $\overline{LOS}$. Constraint (2) ensures that staffing costs do not overrun the budget. In order to reduce the solution space, the amount of assignable staff for each shift is limited by incorporating constraints (3) and (4).

4.2 Simulation Model

Our simulation study is based on the VDI procedure model (VDI 2014). The following sections outline the procedure model phases: data collection, data preparation and system analysis. Furthermore, the verification and validation approach is described.

4.2.1 Data Collection and Preparation

Along the patient's journey through the ED, several activities have to be performed by resources before the patient can be transferred to an inpatient-bed or is allowed to exit the ED. If a group of activities is performed in a row by the same resource(s), the activities can be merged and we consider them as one process step. For instance, taking an X-ray test and discussing test results are separated process steps because they require different rooms and different staff. Therefore, each process step is specified by its predecessor step, successor step, the required resources, and the processing or service time. A chain of those process steps represents a particular patient flow. In order to define patient flows and to collect resources required and service times, patients were observed from arrival to admission or discharge. All patients were assigned to a certain medical specialty. In our study, we take patients of internal medicine and neurology as an example. These two medical specialties are major and non-surgical specialties with similar patient flows. In total, we shadowed 100 and 114 patients assigned to internal medicine and neurology, respectively. Our observation spanned 16 hours from 8 a.m. to 12 p.m. for seven consecutive days. In total, we sampled service times of 78 different process steps. We performed the Kolmogorov-Smirnov test and the Chi-Squared test (α=0.05) as goodness of fit tests for several continuous distributions. Most of the service times can be modeled by using a gamma distribution. Since patients do not always go through all process steps, 5 to 90 data points were used to fit the service time distributions. The median of the number of data points used is 40.

4.2.2 Patient Flow Analysis

Patients are classified into walk-in patients and patients transported by ambulance. They are triaged according to the Manchester-Triage-System (MTS) with scores from 1 to 5. Patients with a score of 1 must be treated most urgently. Additionally, depending on the type of their health conditions, they are assigned to a medical specialty. The patient flow is mainly determined by the previously described attributes. Figure 4 is a coarse-grained description of the modeled patient flow. If patients arrive by ambulance, a nurse or a physician will receive them. Subsequently, they will be assigned to a bed. Parallel, the administrative staff registers them. On the contrary, walk-in patients check in at the reception by themselves. Upon the registration, the patient's MTS score is determined. After triage, patients get treatment and further diagnosis are conducted. A patient with a MTS score of 1 receives preferential treatment in a resuscitation room. In case all resuscitation rooms are occupied, an exam room will be cleared. The probability for demanding a particular activity mainly depends on the medical specialty the patient is assigned to. For instance, blood tests are performed more often for patients of internal medicine than for patients of neurology. Even if a certain activity will be performed for patients of both medical specialties, the service time and the type of the required resources differ. The latter is based on the fact

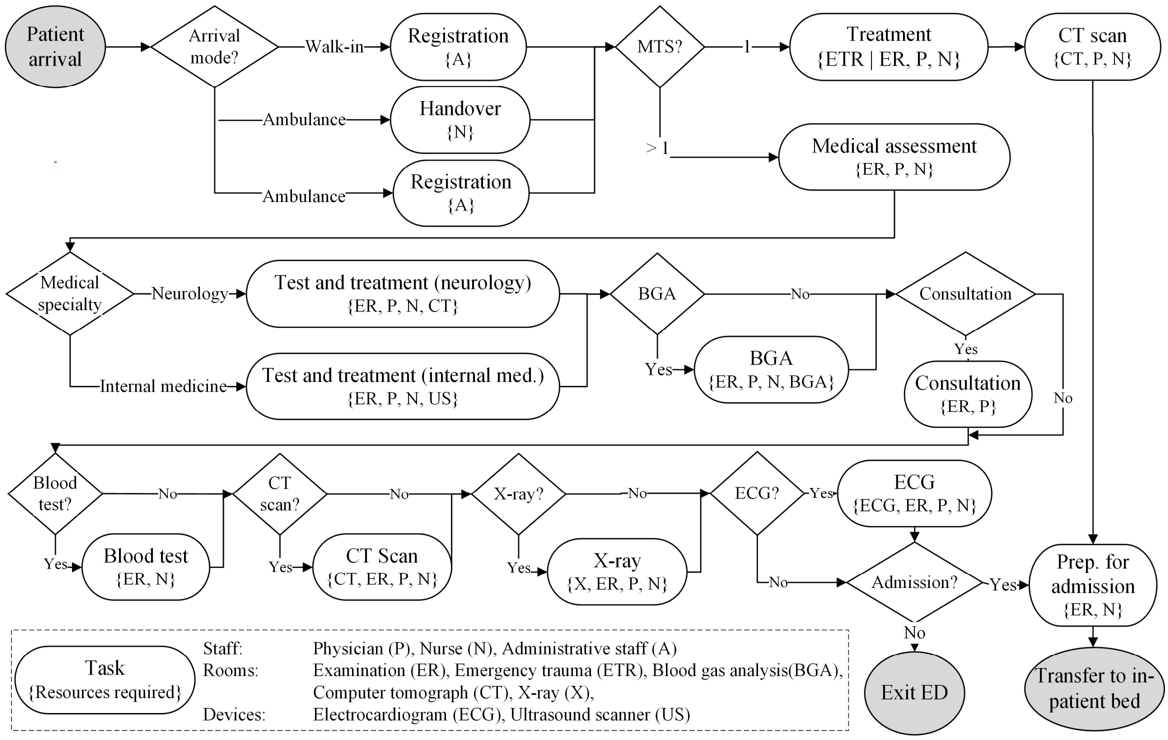

Figure 4: A high-level flow chart of the ED model is shown. It incorporates different patient flows. The tasks shown consolidate multiple process steps, which are specified by a service time and resources required. The resources involved in fulfilling the underlying process steps are parenthesized.

that physicians, exam rooms, and nurses are also dedicated to medical specialties. This results in restricted resource-to-patient assignment possibilities. In addition to the dedicated resources, the simulation model also considers resources shared among medical specialties. Shared resources are administrative staff, an ECG device, an US device, and rooms dedicated to certain diagnosis routines like blood-gas analysis, CT, or X-ray. Regarding the availability of the administrative staff, we simulated arrivals and the registration process step for all patients including patients of other medical specialties. In our model, those patients leave the ED right after registration. With regard to shared devices, we did not further distinguish the availability specifically for internal medicine and neurology patients. First results indicate that this will not influence the observed effects significantly.

4.2.3 Resource-to-patient-assignment Decisions

Usually, a patient enlists a resource's service off and on. In the meantime, the resource provides service to other patients. If several patients are waiting for the same resource, the patients' requests need to be prioritized. To model the ED's resource-to-patient assignment decisions realistically, rules for request prioritization have been gathered based on expert experience. These rules consider characteristics of the patient, the required resources, and the task to be performed. For instance, they incorporate the elapsed time since patient arrival, the MTS score, whether or not the patient has already met a physician, and so on. In order to prevent resources from switching patients after the fulfillment of one process step, the assignment rules also consider whether or not a resource has been seized by a requesting patient previously. Additionally, a patient will always seize the same physician unless the physician's is absent temporarily.

4.2.4 Verification and Validation

According to the procedure model introduced by VDI (2014) all phase results have to be verified and validated. In our simulation study, we iteratively validated the model via, among others, visual checks like tracing a patient agent through the model. With respect to the analysis and experimentation phase, we compared the avg. LOS of internal medicine and neurology patients based on real-world hospital data with the same performance indicators based on output data generated by the verified simulation model. Furthermore, we compared the 0.1-quantile, 0.2-quantile, 0.3-quantile, and so on of the LOS distributions. For this purpose, we used real LOS data of the month of May 2016 because the input data for our experiments is mainly based on hospital data gathered in May 2016.

5 EXPERIMENTS

5.1 Setting

We simulated five weeks excluding a warm-up period of five days. In order to prevent the output data from being biased, the Welch's method (Welch 1983) was used to determine a proper duration for the warm-up period. With respect to that, we performed a series of five replications and we chose a window size (w) of ten for calculating the moving average. Robinson (2004) gives an overview of further methods for determining the warm-up period. Our simulation starts on Sunday 1:00 a.m. and 20 replications with different seeds were performed. Regarding the calculation of the confidence intervals, we chose a significance level (α) of 5% and we used the quantiles of the Student's t-distribution.

For the analysis, we have determined four promising what-if scenarios. Scenario 1 (s1) is the base case, which represents the current setting of the ED. Scenario 2 (s2) studies the impact of pooling of nurses, which have been originally assigned to internal medicine or neurology. In scenario 3 (s3), boarding time is non-existing. Boarding time represents the elapsed time between patient's admission and physical transportation to an in-patient bed. Inpatient boarding is an often stated source of ED overcrowding (Hoot and Aronsky 2008). Therefore, we target quantifying its impact on the avg. LOS. Furthermore, we have observed delays in the treatment process because required treatment material was not ready to hand. Thus, in scenario 4 (s4), we quantify the impact of an optimized material flow by assuming that physicians do not spend any time for looking for treatment material. For each of the four scenarios, we conducted experiments with three different resource settings as shown in Figure 6. Firstly, we considered the current ED staff setting. In order to obtain an improved staff-to-shift allocation (opt. staff), we performed 500 optimization iterations for each of previous described scenarios in OptQuest. In the max. staff setting, the number of available exam rooms for patients of internal medicine and neurology is increased from 6 to 12 and from 3 to 9, respectively. Additionally, the staffing levels are adjusted in a way that each exam room has its own nurse and physician. We observed that the avg. LOS does not continue decreasing if more than 10 (IM) and 6 (NEU) rooms with corresponding staff are available. In the hospital under study, it is common to provide room substitutes if necessary, e.g. during disaster situations. Even though, due to space restrictions, using more than 12 and 9 rooms for the considered medical specialties is not feasible.

5.2 Results and Discussions

If current staffing levels are considered, simulation outputs show that each scenario (s2-s4) leads to an overall reduction in avg. DTD and avg. LOS compared to the base case (s1). An overview of experimental results is presented in Table 2. Figure 5 and Figure 6 show the 95% confidence intervals of the avg. DTD and avg. LOS for neurology patients and internal medicine patients, respectively.

Scenario 2: As expected pooling of nurses improves system efficiency. Compared to the base case, it results in an overall reduction of 27% and 14% in avg. DTD and avg. LOS, respectively. Besides, it increases the amount of patients that meet the 4-h-standard significantly. Interestingly, in s2, the improvement caused by nurse pooling affects patients of internal medicine predominantly. Since, in the base case, the avg. utilization of internal medicine nurses (56%) is significantly higher than the avg. utilization of neurology nurses (19%), balancing workload between these two groups seems to be a promising measure to take. In real life, the pooling of nurses is voluntarily taking place in the daily routine. Among all scenarios, s2 leads to the biggest improvement in avg. DTD and avg. LOS.

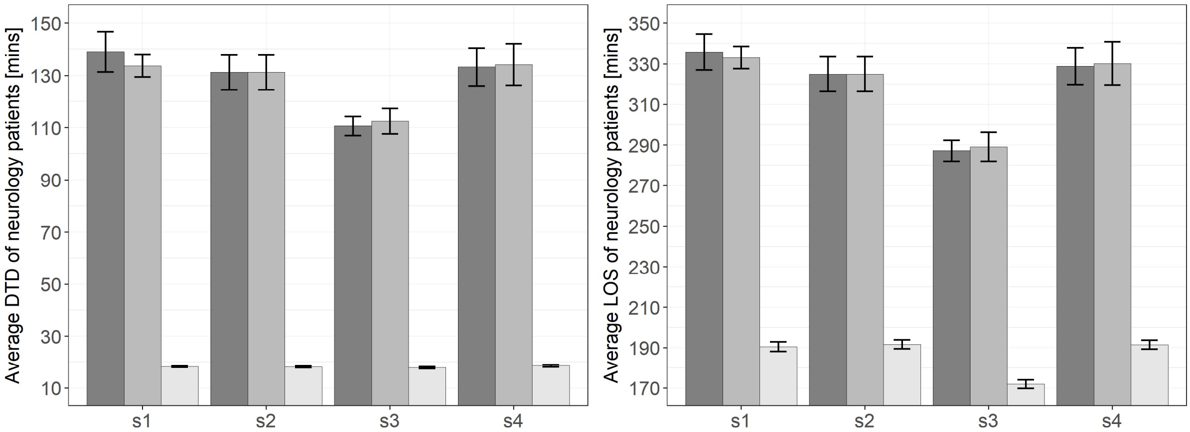

Figure 5: 95% confidence intervals of the avg. LOS and avg. DTD regarding neurology patients only.

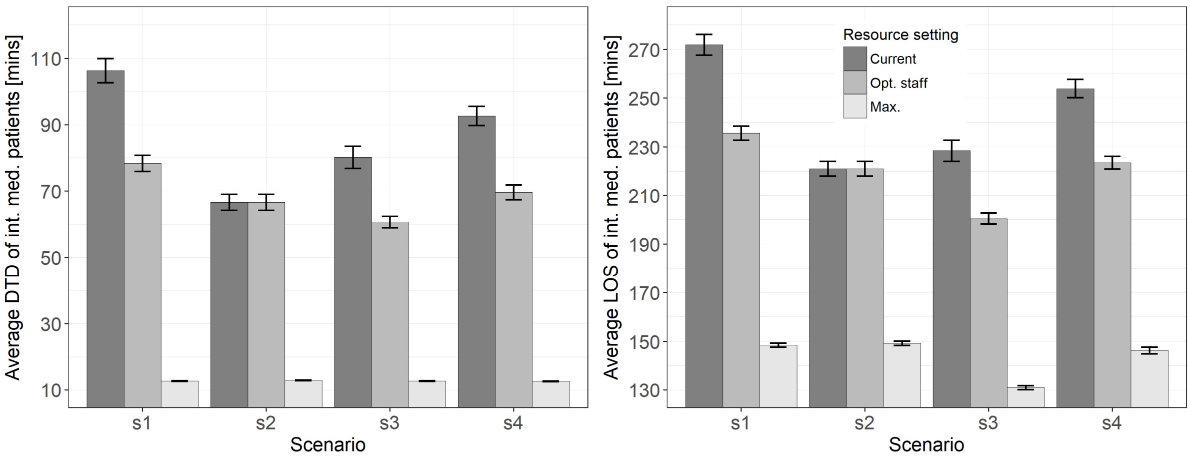

Figure 6: 95% confidence intervals of the avg. LOS and avg. DTD regarding internal med. patients only.

Scenario 3: Preventing ED staff from boarding of in-patients within the ED leads to a 23% reduction in avg. DTD and a 15% reduction in avg. LOS. Regarding the relative amount of patients that meet the 4-h-standard, s3 even outperforms s2. These significant effects unveil a lack of a proper integration of processes across the ED's boundaries. Since the boarding time is caused by the incapability of inpatient wards to move away patients from the ED immediately after their admission, those processes of inpatient wards need to be analyzed as well. Although it is not always feasible to remove patient boarding completely, it is, however, necessary to quantify the effect of patient boarding on the LOS. This quantified evaluation provides valuable motivation for stakeholders and decision makers to take measures for minimizing boarding time.

Scenario 4: A process that does not coerce physicians into searching any kind of treatment material leads to an improvement of 10% in avg. DTD and 5% in avg. LOS. While further analysis is needed for quantifying financial benefits by improving the material flow, this scenario provides a typical real world example. Expensive physician resources are used for extra activities that are waste in view of lean management and in the same time quality is compromised .

Opt. staff: With regard to the optimization of staffing levels, compared to the current resource setting, the number of available nurses for internal medicine patients during day shift is increased from one to two. Besides, the number of available internists during night shift is decreased from two to one. Furthermore, there are only two internists assigned to the short shift compared to five internists in the base case. The number of neurology nurses during short shift is increased from two to four. Therefore, the optimization experiments show that the overall capacity of nurses is increased, whereas the overall capacity of internists is decreased.

Max. resources: It outperforms each scenario of the two other resource settings. Therefore, after optimizing staff levels and improving process efficiency, it is still possible to increase the quality of care significantly by increasing the budget.

Although the process modifications and the optimized staffing levels lead to improvements, Table 2 shows that the results still miss the 4-h-standard by far.

Table 2: An overview of quality metrics (QME) of the experiments. Column "%" indicates the relative change compared to the base case (s1). The resource setting "current" has been used. The measurement unit with respect to the 4-h-standard is the relative frequency of patients that meet the target.

QME	**Med. spec.**	**s1**	**s2**		**s3**		**s4**		**opt. staff for s1**	
DTD (avg.)		**avg.**	**avg.**	**%**	**avg.**	**%**	**avg.**	**%**	**avg.**	**%**
	NEU	139 min.	131	-6%	111	-20%	133	-4%	134	-4%
	IM	106 min.	67	-37%	80	-25%	93	-13%	79	-26%
	Total	115 min.	84	-27%	88	-23%	104	-10%	93	-19%
LOS (avg.)										
	NEU	336 min.	325	-3%	287	-14%	329	-2%	333	-1%
	IM	272 min.	221	-19%	229	-16%	254	-7%	236	-13%
	Total	290 min.	249	-14%	244	-15%	274	-5%	262	-9%
4-h-stand.										
	NEU	40%	42%	+4%	51%	+26%	41%	+2%	40%	0%
	IM	54%	66%	+22%	65%	+20%	57%	+6%	62%	+15%
	Total	50%	59%	+18%	61%	+21%	53%	+5%	56%	+12%

Several unnecessary interruptions within the neurology treatment process have been observed during the shadowing of patients. For instance, neurologists or nurses had to wait for documents or for feedback from imaging or external specialists. Similar to scenario 4, those interruptions might have a major impact on the LOS and should be quantified in future studies.

6 CONCLUSIONS AND FUTURE RESEARCH

We implemented a validated, detailed DES model of a multidisciplinary ED in Germany to provide decision support for ED managers. Our model incorporates several patient flows considering patients and resources of two different medical specialties. The introduced simulation model was parameterized according to real-world data. Leveraging OptQuest and AnyLogic, we combined optimization and simulation to find input staffing levels that minimize the avg. LOS of patients. Simulation experiments show that certain process modifications, nurse pooling, and optimized staffing levels lead to improvements in quality of care. With respect to that, both avoiding boarding of inpatients and implementing nurse pooling result in a decrease of more than 14% in avg. LOS and are particularly promising. We also identified that reallocating capacities from internists to nurses dedicated to internal medicine patients enhances the quality of care.

Our research has some limitations. In real world, certain resources, especially those used for imaging diagnostics, are shared among all medical specialties. To enhance the model's level of detail, all medical specialties should be incorporated in the simulation model. Further research should also consider optimization models that schedule shifts rather than just determining staff levels for fixed shifts. In this study, we have focused on providing quantifications of some ED process improvements rather than introducing a well-tailored simulation optimization approach. Whether a problem specific solution approach can be adapted to optimize staffing in an ED and whether it is more efficient than using a generic solver are questions for our future research.

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APPENDIX

The sets of the staff shifts used in the optimization model are listed in Table 3.

Table 3: Overview of modeled shifts with individual staffing levels.

Symbol	Staff	Set of modeled shifts
$S^{nurse\ neurology}$	Nurse (neurology)	weekdays: {early, day, night, short} weekend: {early, day, night, short}
$S^{nurse\ int.\ med.}$	Nurse (intern. medicine)	weekdays: {early, day, night, short} weekend: {early, day, night, short}
$S^{internist}$	Internist	weekdays: {early, day, night, short}, weekend: {day, night}
$S^{neurologist}$	Neurologist	weekdays: {day, night}, weekend: {day and night}

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