Health Care Manag Sci (2014) 17:1–14
DOI 10.1007/s10729-013-9237-z

An IP-based healthcare provider shift design approach to minimize patient handoffs

Pooyan Kazemian · Yue Dong · Thomas R. Rohleder · Jonathan E. Helm · Mark P. Van Oyen

Received: 1 October 2012 / Accepted: 7 April 2013 / Published online: 28 April 2013

Abstract The new Accreditation Council for Graduate Medical Education (ACGME) duty-hour standards for residents and fellows went into effect in 2011. These regulations were designed to reduce fatigue-related medical errors and improve patient safety. The new shift restrictions, however, have led to more frequent transitions in patient care (handoffs), resulting in greater opportunity for communication breakdowns between caregivers, which correlate with medical errors and adverse events. Recent research has focused on improving the quality of these transitions through standardization of the handoff protocols; however, no attention has been given to reducing the number of transitions in patient care. This research leverages integer programming methods to design a work shift schedule for trainees that minimizes patient handoffs while complying with all ACGME duty-hour standards, providing required coverage, and maintaining physician quality of life. In a case study of redesigning the trainees' schedule for a Mayo Clinic Medical Intensive Care Unit (MICU), we show that the number of patient handoffs can be reduced by 23 % and still meet all required and most desired scheduling constraints. Furthermore, a 48 % reduction in handoffs could be achieved if only the minimum required rules are satisfied.

Keywords Patient handoffs · Scheduling · Integer programming · ACGME duty-hour standards · Shift design · Shift assignment

P. Kazemian · M. P. Van Oyen (✉)
Department of Industrial and Operations Engineering, University of Michigan, 1205 Beal Ave.,
Ann Arbor, MI 48109, USA
e-mail: vanoyen@umich.edu

P. Kazemian
e-mail: pooyan@umich.edu

Y. Dong
Multidisciplinary Simulation Center,
Mayo Clinic, 200 First St. SW,
Rochester, MN 55905, USA
e-mail: dong.yue@mayo.edu

T. R. Rohleder
Department of Health Sciences Research, Center for the Science of Health Care Delivery, Mayo Clinic, 200 First St. SW,
Rochester, MN 55905, USA
e-mail: rohleder@mayo.edu

J. E. Helm
Kelley School of Business, Indiana University,
1309 East Tenth St.,
Bloomington, IN 47405, USA
e-mail: helmj@indiana.edu

1 Introduction and background

In November 1999, the U.S. Institute of Medicine (IOM) issued a report on medical errors estimating that nearly 100,000 patients die each year as a result of medical errors and another 15 million are harmed [1]. Root cause analysis of reported sentinel events from 1994 to 2004 revealed that two-thirds of these errors were due to communication failures [2]. According to Dr. Lucien Leape, the number of deaths from medical errors in hospitals is equivalent to the death toll from three jumbo jet crashes every 2 days [3]. In fact, more people die as a result of medical errors than from motor vehicle accidents, breast cancer, or AIDS. Recent reports continue to support the initial findings from IOM [4] and connect fatigue-related medical errors with residents' duty hours [5].

In September 2010, the Accreditation Council for Graduate Medical Education (ACGME) enacted new duty-hour regulations for residents and fellows [6] that limited weekly work hours, length of duty periods, off time between shifts, and frequency of consecutive working days and nights. These stricter duty-hour requirements went into effect on July 1, 2011 [7]. The goal was to reduce fatigue-related medical errors and improve patient safety by limiting residents/fellows (trainees) work hours. However, the more restrictive shifts have resulted in a significant increase in patient *handoffs* and communication failures [8–13]. Patient handoff is defined as "the process of transferring primary authority and responsibility for providing clinical care to a patient from one departing caregiver to one oncoming caregiver" [14]. Some other terms that have commonly been used for handoff in the literature are *handover*, *sign-out*, *turnover*, *transition of care*, *transfer of care* and *shift change transfer*. It is worth noting that the working shifts of both residents and fellows must comply with the ACGME duty hour regulations. For ease of reference, we use the term "trainees" to refer to both residents and fellows in the rest of the paper. We also refer to postgraduate year 2 (PGY-2) and above residents and all fellows as "senior trainees".

Several studies have correlated increased patient handoffs with more medical errors caused by communication breakdowns and therefore worse patient outcomes [15–25]. It is believed that 20 %–30 % of information conveyed during patient handoffs is not documented in the medical record [15, 26]. Figure 1 depicts the connection between the new ACGME duty-hour regulations and medical errors.

Several studies have focused on the communication aspects of handoffs and have provided recommendations to achieve high quality handoffs [8, 27–37]. For example, Kemp et al. [37] presented a methodology for conducting safe and effective sign-outs in a surgical service. Clark et al. [38] designed a sign-out template to standardize the handoff process in a general surgery residency program. Other studies have focused on the overall handoff process. For instance, Abraham et al. [39] proposed a clinician-centered approach that captures the entire clinician workflow prior to, during, and after handoff communication. Most of these studies have employed interviews, surveys, and observations to understand handoff failures and provide suggestions to enhance handoff fidelity.

While a high-quality, structured handoff process is important, decreasing number of patient handoffs is an additional and fundamental way to reduce opportunities for medical errors caused by communication breakdowns, supporting safer and more efficient patient care. The new ACGME duty-hour standards themselves specifically emphasize the importance of reducing handoffs (section VI.B.1. of [7]):

> "Programs must design clinical assignments to minimize the number of transitions in patient care."

Borman et al. [40] recently surveyed surgery residents and identified that resident perceptions of causes of medical errors suggest that system changes are more likely to enhance patient safety than further hour limits. This research provides mathematical methods for effecting such system change, by redesigning schedules to reduce the number of patient handoffs, hence reducing the opportunity for communication error.

While recent research has focused on improving the quality of communication during the handoff process (i.e. improving box 6 in Fig. 1) to reduce medical errors caused by communication breakdowns, to the best of our knowledge, no prior work leverages physician scheduling to reduce the quantity of handoffs (i.e. improving box 5 in Fig. 1). This research contributes to the handoff literature by providing an Integer Programming (IP) approach to design trainees' schedules in a patient-centered manner that minimizes number of handoffs while respecting ACGME duty-hour standards.

The methodology we develop is highly generalizable and, while the proof of concept is developed for an Intensive Care Unit (ICU), our approach can be applied to many different care units in hospitals, including different intensive care unit types (e.g. Medical ICU, Surgical ICU, Pediatric ICU, Critical Care Unit, etc.), the emergency department, and general floor care (internal medicine or surgery). This approach can also be employed for different provider levels, e.g. attending physicians, fellows, residents, nurses, etc.

Mathematical optimization techniques have been widely used to solve the physician and nurse scheduling problems in a provider-centered manner [41–44]. In the "physician scheduling problem", given a set of doctors, a set of shifts and a planning period, one seeks to find fair schedules for all physicians [45]. In the nurse scheduling problem, the cost of salaries should also be minimized.

Several studies have employed integer programming to formulate and solve the physician and nurse scheduling

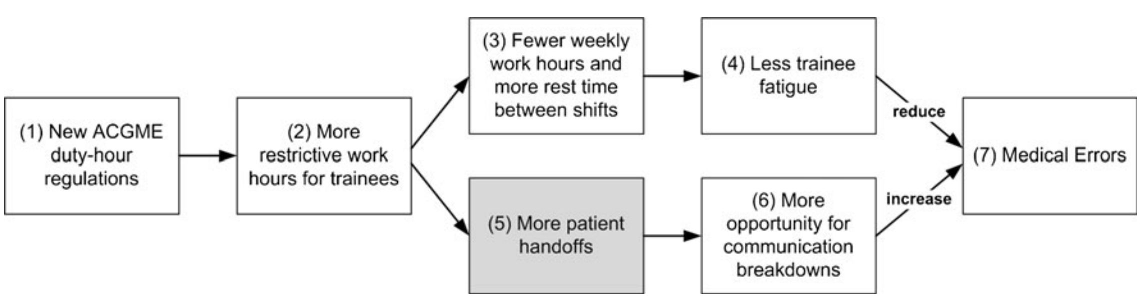


Fig. 1 Connection between ACGME standards and medical errors—the net effect is uncertain

problems [46–50]. These studies provide mathematical models to assign healthcare providers to pre-determined fixed shifts (i.e. shift assignment models).

Gascon et al. [46] studied the flying squad nurse scheduling problem. A multi-objective integer programming problem with binary variables was employed to find a feasible schedule satisfying most of the constraints. The paper combined the sequential and the weighted method to obtain the best nurse schedule for minimizing the deviation measures in soft constraints. Bard and Purnomo [47] developed an integer programming model to produce a revised schedule for regular and pool nurses to efficiently use them in the event of surge in demand for nursing services. The objective is to achieve sufficient coverage with the minimum cost of revising nurses' schedules. Beaulieu et al. [48] addressed the problem of physician scheduling. This paper employed integer programming to make a schedule for physicians in the emergency room of a major hospital in Montreal, Canada. The model was able to generate a better schedule with smaller deviations from desired metrics in much shorter amount of time than the current method being used by hospital staff. Sherali et al. [49] proposed mixed-integer programming models to address the resident scheduling problem concerned with prescribing work-nights for residents. Heuristic solution approaches were developed to solve the problem under different scenarios. Cohn et al. [50] also combined IP-based techniques with user expertise and heuristic approaches to construct high-quality schedules for residents in the psychiatry program at Boston University School of Medicine based on their individual preferences.

Our IP-based shift "design and assignment" model differs in that it simultaneously (1) finds the best times for starting and ending the shifts to minimize the number of patient handoffs (this is the shift design part), and (2) assigns physicians to the shifts such that all ACGME duty-hour regulations are satisfied, required coverage is achieved, and livability rules are met (this is the shift assignment part).

The shift design concept brings a new perspective to the problem of how best to incorporate the ACGME rules and provides a systematic, model-driven method for *designing* physicians' schedules compared to the conventional approach of selecting between either two 12-h shifts or three 8-h shifts per day. It further benefits patients by minimizing error-contributing handoffs while maintaining physicians' quality of life.

The rest of the paper proceeds as follows. In Section 2, we present the general model for designing the work shift schedule for healthcare providers. In Section 3, we provide a proof of concept by applying the model in a case study in the Medical Intensive Care Unit (MICU) at Saint Marys Hospital using historical data to demonstrate the benefits of our methodology. Section 4 provides suggestions for future work and section 5 presents the conclusions from this work.

2 Model development

In this section we present model assumptions, sets, parameters, variables, constraints and objective function. The parametric model in this section is based on the ICU setting for scheduling trainees at the Mayo Clinic; however, the same model (perhaps with slight modification) could be used for other hospital care units.

2.1 Assumptions

Because of the IP framework and also to ensure tractable and practical solutions, it is necessary to divide each day into discrete time blocks and to assume that shift change can happen only at the start/end of these time blocks. For example, if a day is divided evenly into 6 time blocks, each block would be 4 h and shift changes can occur only at times 0, 4, 8, 12, 16 and 20. In other words, each physician can either work or not work in a full time block. We also approximate the number of patients handed off in each shift change based on historical data on ICU patient census by time of day and day of week.

2.2 Sets and parameters

We use the following sets in our model.

- I set of trainees
- J set of days within the planning horizon
- T set of weeks within the planning horizon
- K set of time blocks within a day
- Kn set of time blocks corresponding to night shift
- Kr set of time blocks that end during rounding time interval
- $Kinc$ set of time blocks that end during inconvenient time interval for shift change (usually considered as late night and early morning).

The main model parameters are listed below.

- NbF number of trainees (fellows or residents)
- NbD number of days within the planning horizon
- NbW number of weeks within the planning horizon
- NbB number of time blocks within a day
- ShL maximum shift length allowed in hours
- c_{jk} approximate number of patient handoffs incurred by a shift change at the end of time block k in day j, calculated based on the average number of patients in the ICU at the time of shift change
- d_{jk} minimum number of trainees required to be in the hospital at time block k of day j.

We also use a few auxiliary parameters in our model to simplify the notation. They are directly calculated from the main parameters.

$BL = \frac{24}{NbB}$ length of each time block in hours

$B^{ShL} = \left\lfloor \frac{ShL}{BL} \right\rfloor$ maximum number of consecutive time blocks which do not exceed ShL hours

$B_{10} = \lceil 10/BL \rceil$ minimum number of consecutive time blocks which exceed 10 h.

2.3 Decision variables

The following decision variables are used in the model.

x_{ijk} 1 if trainee i is assigned to time block k on day j, and 0 otherwise

y_{jk} 1 if there is a shift change at the end of time block k on day j, and 0 otherwise

z_{ij} 1 if trainee i is totally off-duty on day j, and 0 otherwise

w_{ij} 1 if trainee i works at night on day j, and 0 otherwise.

2.4 Constraints

The model constraints can be classified into three categories: (1) required and (2) desirable constraints are associated with mandatory and optional scheduling rules respectively, while (3) linkage constraints enforce model dynamics.

2.4.1 Required constraints

Certain constraints are required by regulation or organizational policy. The first five of these constraints are required by ACGME duty-hour regulations, while 6 and 7 are required by organizational policy.

1. Duty periods of postgraduate year 1 (PGY-1) residents must not exceed 16 h in duration; however, senior trainees may be scheduled to a maximum of 24 h of continuous duty. The following inequalities ensure that trainees do not work shifts longer than ShL hours. ShL is the maximum shift length allowed in hours so we use this value as an upper bound for shift length.

$$\sum_{k=s}^{B^{ShL}+s} x_{ijk} \le \frac{ShL}{BL} \qquad \forall i \in I,\ \forall j \in J,\ \forall s \in \left\{1, \ldots, \left(NbB - B^{ShL}\right)\right\}, \tag{1}$$

$$\sum_{k=s}^{NbB} x_{ijk} + \sum_{k=1}^{s-\left(NbB-B^{ShL}\right)} x_{i,j+1,k} \le \frac{ShL}{BL} \qquad \forall i \in I,\ \forall j \in \{1, \ldots, NbD-1\},\ \forall s \in \left\{\left(NbB - B^{ShL}\right)+1, \ldots, NbB\right\}. \tag{2}$$

If ShL=24 (i.e. the maximum allowed shift length is 24 h), inequality (1) is not needed and only inequality (2) is kept.

2. Weekly duty hours must not exceed 80 h:

$$\sum_{j=7(t-1)+1}^{7t} \sum_{k \in K} x_{ijk} \le \frac{80}{BL} \qquad \forall i \in I,\ \forall t \in T. \tag{3}$$

3. Trainees must have a minimum of 10 h free of duty between scheduled duty periods:

$$x_{i,j,k} - x_{i,j,k+1} + x_{i,j,k+s+2} \le 1 \qquad \forall i \in I,\ \forall j \in J,\ \forall k \in \{1, \ldots, NbB - B_{10}\},\ \forall s \in \{0, \ldots, B_{10} - 2\}, \tag{4}$$

$$x_{i,j,k} - x_{i,j,k+1} + x_{i,j,k+s+1} \le 1 \qquad \forall i \in I,\ \forall j \in J,\ \forall k \in \{NbB - B_{10} + 1, \ldots, NbB - 1\},\ \forall s \in \{0, \ldots, (NbB - 1) - k\}, \tag{5}$$

$$x_{i,j,k} - x_{i,j,k+1} + x_{i,j+1,s+1} \le 1 \qquad \forall i \in I,\ \forall j \in \{1, \ldots, NbD - 1\},\ \forall k \in \{NbB - B_{10} + 1, \ldots, NbB - 1\},\ \forall s \in \{0, \ldots, k - (NbB - B_{10} + 1)\}, \tag{6}$$

$$x_{i,j,NbB} - x_{i,j+1,1} + x_{i,j+1,s+2} \le 1 \qquad \forall i \in I,\ \forall j \in \{1, \ldots, NbD - 1\},\ \forall s \in \{0, \ldots, B_{10} - 2\}. \tag{7}$$

If $NbB \ge 3$, inequalities (4) – (7) are required. Otherwise, this rule is automatically satisfied by other required constraints and the above inequalities are not needed to make sure trainees will get at least 10 h off between shifts.

4. Trainees must get at least 1 day off per 7-day period (when averaged over 4 weeks):

$$\sum_{j=7(t-1)+1}^{7(t-1)+28} z_{ij} \ge 4 \qquad \forall i \in I,\ \forall t \in \{1, \ldots, NbW - 3\}. \tag{8}$$

5. Trainees must not be scheduled for more than 6 consecutive shifts of night duty (night float):

$$\sum_{s=0}^{6} w_{i,j+s} \le 6 \qquad \forall i \in I,\ \forall j \in \{1, \ldots, NbD - 6\}. \tag{9}$$

6. The required coverage must be satisfied (coverage constraint):

$$\sum_{i \in I} x_{ijk} \geq d_{jk} \qquad \forall j \in J,\ \forall k \in K. \tag{10}$$

7. Shift change is not allowed during bedside multidisciplinary rounds because this would disrupt the rounding process and impact the educational benefit to trainees:

$$y_{jk} = 0 \qquad \forall j \in J,\ \forall k \in Kr. \tag{11}$$

2.4.2 Linkage constraints

The following inequalities serve as linkage constraints to connect x, y, z and w variables.

1. Inequalities (12) – (15) ensure that whenever there is a shift change at the end of time block k on day j, variable y_{jk} is assigned value 1.

$$y_{jk} \geq x_{ijk} - x_{i,j,k+1} \qquad \forall i \in I,\ \forall j \in J,\ \forall k \in \{1, \ldots, NbB - 1\}, \tag{12}$$

$$y_{jk} \geq x_{i,j,k+1} - x_{ijk} \qquad \forall i \in I,\ \forall j \in J,\ \forall k \in \{1, \ldots, NbB - 1\}, \tag{13}$$

$$y_{j,NbB} \geq x_{i,j,NbB} - x_{i,j+1,1} \qquad \forall i \in I,\ \forall j \in \{1, \ldots, NbD - 1\}, \tag{14}$$

$$y_{j,NbB} \geq x_{i,j+1,1} - x_{i,j,NbB} \qquad \forall i \in I,\ \forall j \in \{1, \ldots, NbD - 1\}. \tag{15}$$

2. Inequality (16) ensures that whenever z_{ij} is 1, trainee i is off-duty on day j.

$$\sum_{k \in K} x_{ijk} \leq NbB\left(1 - z_{ij}\right) \qquad \forall i \in I,\ \forall j \in J. \tag{16}$$

3. Inequalities (17) and (18) ensure that w_{ij} is 1 when trainee i works at night on day j, and 0 otherwise.

$$x_{ijk} \leq w_{ij} \qquad \forall i \in I,\ \forall j \in J,\ \forall k \in Kn, \tag{17}$$

$$w_{ij} \leq \sum_{k \in Kn} x_{ijk} \qquad \forall i \in I,\ \forall j \in J. \tag{18}$$

2.4.3 Desired constraints

In addition to the required constraints, there are some other characteristics for a schedule which are not required, but are desirable to obtain more convenient and livable schedules. These could include vacation requests, sleep hours, circadian rhythm or other human factors issues. In this part, we discuss the desired constraints in our model. These rules have been developed through several meetings and discussions with program directors, consultants, chief residents and fellows at Mayo Clinic.

1. To maintain regular sleep hours for trainees, we disallow shift changes at late night or early morning (inconvenient times).

$$y_{jk} = 0 \qquad \forall j \in J,\ \forall k \in Kinc. \tag{19}$$

2. ACGME rules only require 1 day off per 7-day period (when averaged over 4 weeks). However, working several days in a row could cause fatigue, irritability and reduced concentration for trainees. Hence, the desire is to provide at least 1 day off per any 7-day period (without averaging). This means that, trainees are permitted to work no more than 6 days in a row.

$$\sum_{s=0}^{6} z_{i,j+s} \geq 1 \qquad \forall i \in I,\ \forall j \in \{1, \ldots, NbD - 6\}. \tag{20}$$

3. Based on ACGME regulations, trainees are allowed to work for up to six consecutive night shifts. Nevertheless, it is believed that doing a lengthy run of night shifts might be associated with extreme fatigue, insomnia, and sleep deprivation. Hence, we limit the night float to a maximum of four consecutive night shifts.

$$\sum_{s=0}^{4} w_{i,j+s} \leq 4 \qquad \forall i \in I,\ \forall j \in \{1, \ldots, NbD - 4\}. \tag{21}$$

4. The minimum required off-time between scheduled duty periods is considered as 10 h by ACGME. However, switching to day time work after doing a run of night shifts is hard for human brain. Preferably, trainees would have at least one whole day off (in addition to the post-call day) after doing a run of night shifts to better adjust their sleep pattern.

   The following inequality ensures that after each night shift, either another night shift or a day off should be assigned to trainees.

$$w_{ij} - w_{i,j+1} - z_{i,j+1} \leq 0 \qquad \forall i \in I,\ \forall j \in \{1, \ldots, NbD - 1\}. \tag{22}$$

5. Although ACGME duty hour regulations allow a shift to last up to 16 h for PGY-1 and 24 h for PGY-2 and above, shifts longer than 12 h are believed to be associated with fatigue, headaches, irritability and reduced concentration.

Table 1 Scheduling constraints: required constraints (RC) and desired constraints (DC)

Scheduling Constraints	
RC1	Trainees must not work longer than *ShL* hours on a single shift.
RC2	Trainees must not work more than 80 h per week.
RC3	Trainees must get at least 10 h off-duty between shifts.
RC4	Trainees must get at least 1 day off per 7 days (averaged over 4 weeks).
RC5	Trainees must not be scheduled for more than six consecutive night shifts.
RC6	The required coverage must be satisfied.
RC7	Shift change is not allowed during bedside multi-disciplinary rounds.
DC1	Shift change is not allowed at late night or early morning (inconvenient times).
DC2	Trainees should not work more than 6 days in a row.
DC3	Trainees work no more than four night shifts in a row.
DC4	Trainees have at least 1 day off after a run of night shifts.
DC5	Shifts longer than 12 h are not allowed.

Hence, we limit the shift length to 12 h by setting the value of *ShL* parameter to 12 in inequalities (1) and (2).

To summarize our discussion in this section, all the “Required Constraints” (RCs) and “Desired Constraints” (DCs) are listed in Table 1.

2.5 Objective function

The objective is to minimize the approximate number of patient handoffs during the scheduling horizon, calculated based on the average ICU patient census at the time of shift change. Figure 2 provides two examples of how the number of patient handoffs is affected by the number of patients in the ICU. In Fig. 2a, there are two shift changes (provider transfers) at 7 am/pm. At the 7 am shift change there are two patients in ICU, so we incur two handoffs, while at 7 pm there is one patient in ICU and we incur one handoff. Figure 2b illustrates the same scenario, but with only one shift change at noon, where 4 patients are handed off. Clearly, minimizing number of patient handoffs is not equivalent to minimizing number of shift changes. Furthermore, longer shifts do not guarantee fewer handoffs as seen in the example of Fig. 2 (which also illustrates how the number of handoffs is calculated in our model). The challenge lies in designing a schedule that complies with all required constraints (and preferably most desired constraints) in a way that fewer patients have to be handed off. The objective function can be written as follows:

$$\min \sum_{j\in J}\sum_{k\in K} c_{jk}y_{jk} \ . \tag{23}$$

3 Case study

This section presents a detailed discussion of how our model can be applied in a healthcare setting to help redesign trainees’ work shifts to minimize the number of patient handoffs. We applied our model to the Medical Intensive Care Unit (MICU) at Saint Marys hospital in Rochester, Minnesota operated by Mayo Clinic. The MICU at Saint Marys hospital is a 24-bed unit. Our focus is on redesigning the fellows’ shifts, as their service has the most impact on patient outcomes. Similar analysis can be applied to other provider levels (e.g., residents, attending consultants, etc.) and other hospital units as well.

3.1 Assumptions

The detailed parameterization of the model for the case study was obtained through several meetings with resi-

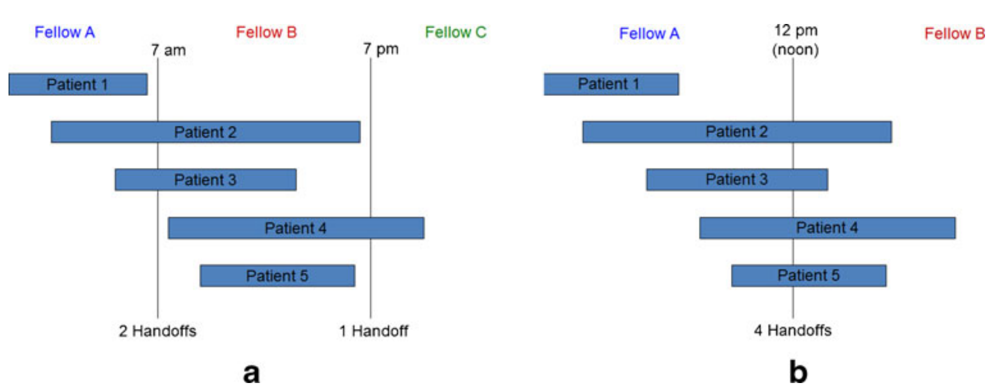


Fig. 2 Examples of how the number of patient handoffs is calculated in the performance analysis model: (**a**) 2 shift changes and 3 patient handoffs, (**b**) 1 shift change and 4 patient handoffs

dency and fellowship program directors, chief residents and fellows, as well as feedback from different medical providers at Mayo Clinic.

For the case study, we consider a 4-week scheduling horizon which starts on a Saturday and ends on a Friday as trainees at Mayo Clinic rotate between different units every 4 weeks. Two years of MICU admission and discharge data were used to calculate the approximate MICU census for different days of week and times of day.

Each day was divided into 12 time blocks. Hence, shift changes can happen at any of times 0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20 and 22 in military time format. One nice property of the 2-h time block is that, for this case study, the resulting schedule has a symmetric structure. The symmetric structure of our proposed schedule makes it easy to remember and much more appealing for implementation.

Based on ACGME rules, the maximum shift length is 16 h for postgraduate year 1 (PGY-1) residents and 24 h for senior trainees. Because the 24-h shifts are believed to cause extreme tiredness and sleep deprivation contributing to more fatigue-related medical errors and poor patient outcomes, we limit the maximum shift length to 16 h for fellows. Currently fellows work 12-h shifts in the MICU. We start our analysis with a 16-h limit on shift length, but will perform a sensitivity analysis on shorter and longer shifts later.

Some constraints deal with night shifts (i.e. inequalities (9), (17), (18) and (22)). In our study, we define night to be from 10:00 pm to 6:00 am. Hence, if a fellow is working at any time in this interval, we assume he/she is on a night shift.

To provide 24/7 coverage, at least three fellows are required. This is because each fellow can work a maximum of 80 h per week and we want to provide $24*7=168$ h weekly coverage. Hence, we need at least $\left\lceil \frac{168}{80} \right\rceil = 3$ fellows.

For inequality (11), which ensures there is no shift change during the bedside multi-disciplinary rounds, we need to determine the set of time blocks that end during this interval. Currently, the bedside rounds happen from 8:30 am to 11:00 am in the MICU.

Finally, a shift change is not allowed at inconvenient times (late night and early morning) through inequality (19). In this case study, we assume any time after 10:00 pm and before 4:00 am is inconvenient for a shift change.

3.2 Set and parameter values

Based on our previous discussion, model sets and parameters are assigned the following values.

Sets:

$I=\{1, 2, 3\}$,
$J=\{1, 2, \ldots, 28\}$,
$T=\{1, 2, 3, 4\}$,
$K=\{1, 2, \ldots, 12\}$,
$Kn=\{1, 2, 3, 12\}$,
$Kr=\{5\}$,
$Kinc=\{1, 2, 12\}$.

Parameters:

$NbF=3$,
$NbD=28$,
$NbW=4$,
$NbB=12$,

$$ShL = \begin{cases} 12 & \text{if DC5 is included in the scenario under consideration} \\ 16 & \text{Otherwise} \end{cases},$$

$$d_{jk} = 1 \qquad \forall j \in J,\ \forall k \in K,$$

$$BL = \frac{24}{NbB} = 2,$$

$$B^{ShL} = \left\lfloor \frac{ShL}{BL} \right\rfloor = 8,$$

$$B_{10} = \lceil 10/BL \rceil = 5.$$

c_{jk} is equal to the average MICU patient census at the end of time block k in day j.

3.3 Data collection

We used 2 years of MICU admission and discharge data to obtain patient census profiled by time of day and day of week. A computer program was developed to extract the required data from the dataset and to keep track of patient admissions and discharges for each time block of every day. Figure 3 shows the average MICU admission and discharge patterns during the day. As seen in this graph, there are almost no discharges at nights. Bedside rounds start at 8:30 am during which the discharge decisions are made by the team of residents, fellows and consultants. Patient discharges typically start around 9:00 am. The admission process is smoother with a higher average during the daytime. Figures 4 and 5 show the average MICU patient census versus different times of day and days of week. Mornings are more crowded than evenings since there is no discharge from the MICU at nights and before the rounds start in the morning. These results make sense intuitively and are in line

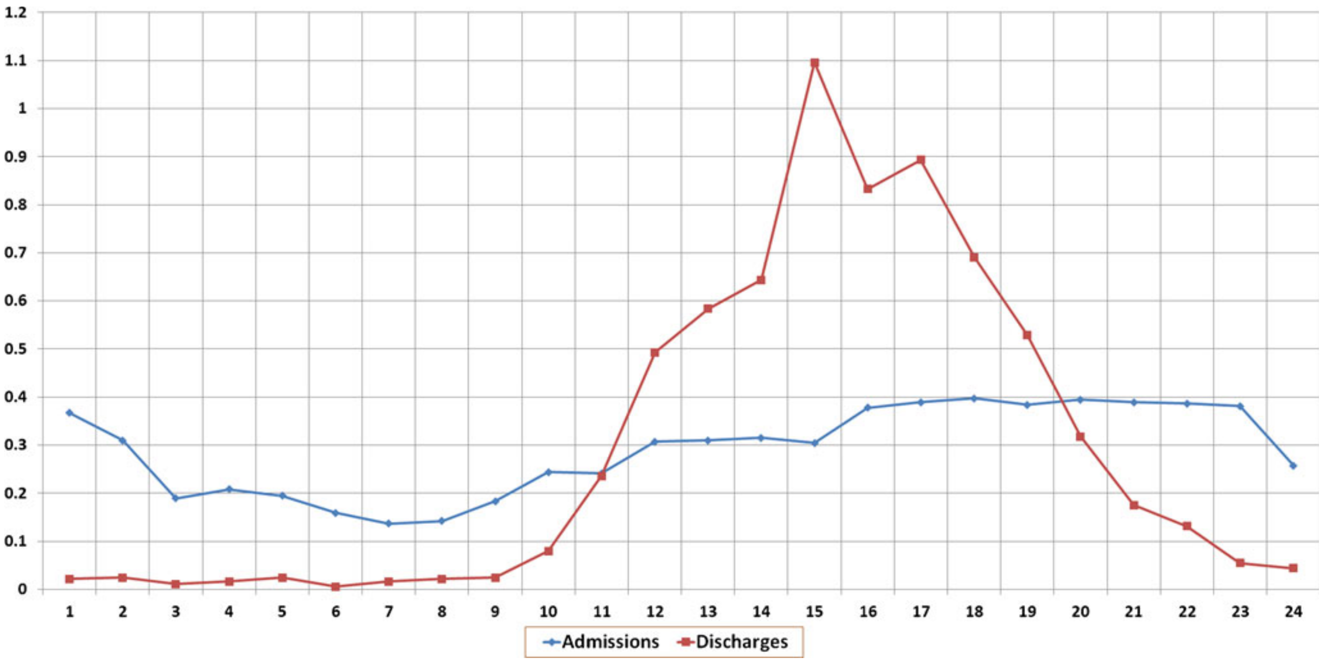


Fig. 3 MICU admissions and discharges

with expert opinion which supports our data collection. Although the MICU census fluctuates from month to month, the pattern for different times of day and different days of week is similar. Since the census pattern is what matters for our shift design study (rather than the actual census numbers), we take the grand average census over months of year and use these numbers to approximate number of patient handoffs in our data-driven numerical analysis.

3.4 Experimental scenarios

In this section, we solve the scheduling problem for different combinations of constraints to determine their effect on the objective function. The intent is to determine which desired constraints have the most impact on the number of patient handoffs.

As discussed in section 2.4, required constraints are those constraints that must be enforced in order to obtain valid or

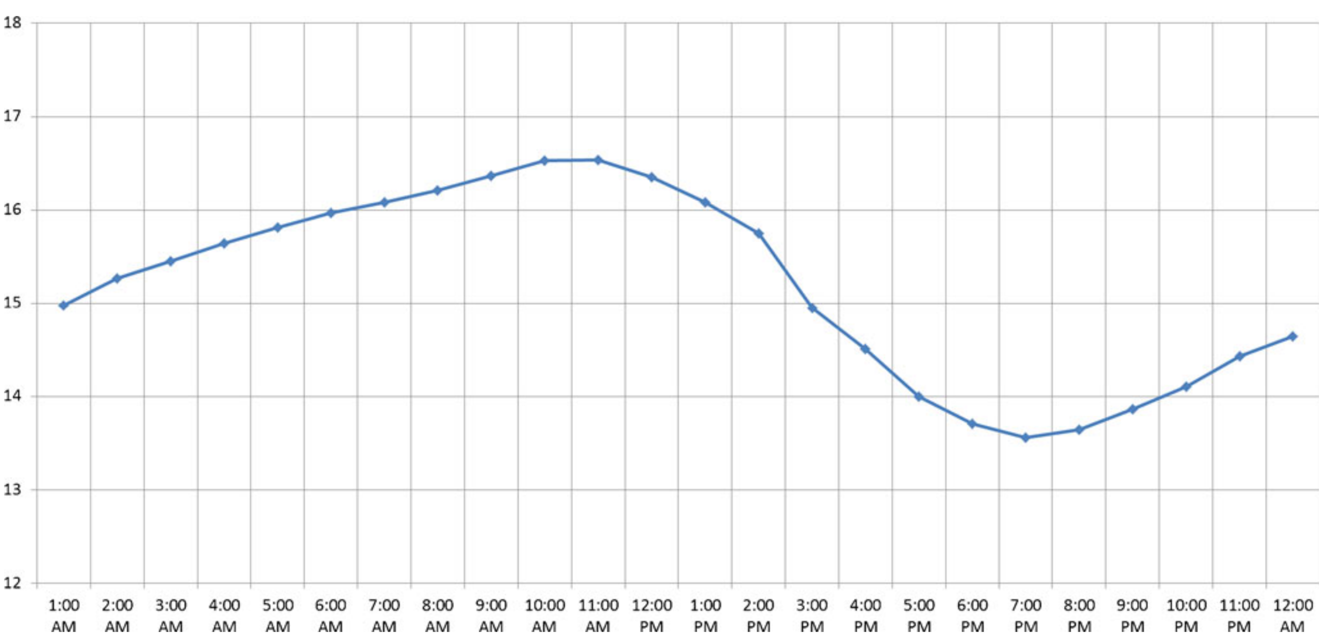


Fig. 4 Average MICU patient census vs. time of day

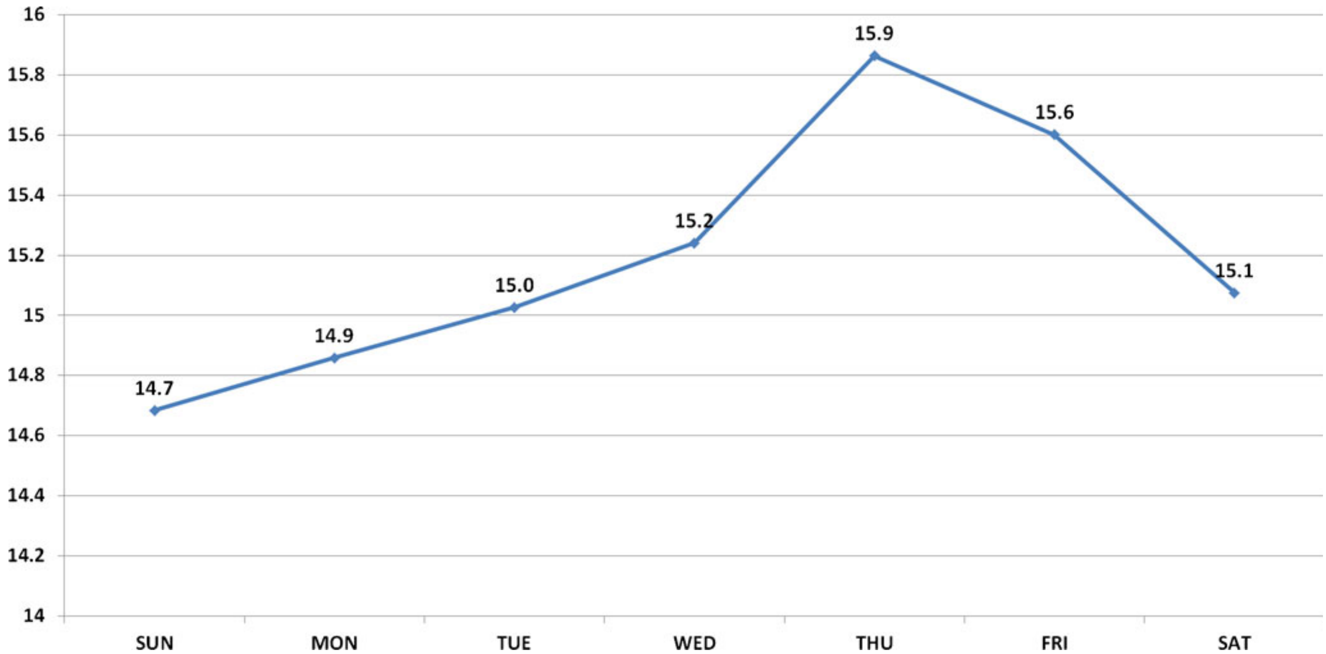


Fig. 5 Average MICU patient census vs. day of week

feasible schedules. Desired constraints are not required to be satisfied, but they make the resulting schedule more appealing. We perform our analysis by adding one or a combination of desired constraints to the model and study their impact on the objective value (number of patient handoffs). If a desired constraint results in a great increase in the number of patient handoffs, loosening its bound or removing it will help avoid an increase in handoffs. This provides insight into the relative cost in terms of handoffs of a desired constraint.

There are 32 combinations of the five desired constraints. Those include having no desired constraints satisfied (1 case), having one desired constraint satisfied (5 cases), and so on. We will show the approximate number of patient handoffs for each case later in this section. First, we start with two extreme cases.

Scenario A—only required constraints The first scenario we investigate is the case in which only required constraints are satisfied. The resulting schedule will provide a lower bound on the minimum achievable number of handoffs. The number of patient handoffs from this case is used as the baseline for our comparison. The solution yields 635 patient handoffs over the 4-week scheduling horizon.

Scenario B—All required constraints and all desired constraints The second scenario we study is the case in which all required and desired constraints are satisfied. This provides an upper bound on the number of patient handoffs. Interestingly, the resulting schedule was the same as current MICU schedule with 831 patients handed off during the 4-week horizon. The cost of having all desired constraints satisfied is a 31 % increase in the number of patient handoffs.

Scenario C—All required constraints together with one desired constraint The previous scenarios provide a lower and an upper bound for the number of patient handoffs (635 and 831 respectively). In this scenario, we study the impact of each desired constraint on the number of patient handoffs by including them in the model individually. Scenarios C_1, C_2, C_3, C_4 and C_5 are related to the cases in which DC1, DC2, DC3, DC4 and DC5 are added to the model respectively. The results show that adding DC2 or DC4 does not increase the number of patient handoffs, while adding DC1 or DC3 results in 641 patient handoffs (1 % increase). On the other hand, adding DC5 (limiting shift length to 12 h) results in 831 patient handoffs, the same result as the upper bound.

Scenario D—All required constraints together with DC1-DC4 The results of previous scenarios revealed that each of these constraints individually does not significantly degrade the objective function. Including all of them simultaneously leads to a schedule with 641 patient handoffs on average over the 4-week horizon. This is only 1 % greater than the lower bound (Scenario A), which includes none of the desired constraints.

Scenario E—All required constraints together with DC2 and DC4 In scenario C, we saw that adding DC2 or DC4 to the model one at a time would not increase the number of

Table 2 Summary of results of experimental scenarios

Case #	Scenario	Desired Constraints	Number of Patient Handoffs	Dominated By Scenario
1	A	–	635 (baseline)	C_2 & C_4
2	C_1	1	641 (+1 %)	D
3	C_2	2	635 (+0 %)	
4	C_3	3	641 (+1 %)	D
5	C_4	4	635 (+0 %)	
6	C_5	5	831 (+31 %)	B
7		1, 2	≥ 641	D
8		1, 3	≥ 641	D
9		1, 4	≥ 641	D
10		1, 5	≥ 831	B
11		2, 3	≥ 641	D
12	E	2, 4	641 (+1 %)	D
13		2, 5	≥ 831	B
14		3, 4	≥ 641	D
15		3, 5	≥ 831	B
16		4, 5	≥ 831	B
17		1, 2, 3	≥ 641	D
18		1, 2, 4	≥ 641	D
19		1, 2, 5	≥ 831	B
20		1, 3, 4	≥ 641	D
21		1, 3, 5	≥ 831	B
22		1, 4, 5	≥ 831	B
23		2, 3, 4	≥ 641	D
24		2, 3, 5	≥ 831	B
25		2, 4, 5	≥ 831	B
26		3, 4, 5	≥ 831	B
27	D	1, 2, 3, 4	641 (+1 %)	
28		1, 2, 3, 5	≥ 831	B
29		1, 2, 4, 5	≥ 831	B
30		1, 3, 4, 5	≥ 831	B
31		2, 3, 4, 5	≥ 831	B
32	B	1, 2, 3, 4, 5	831 (+31 %)	

patient handoffs. In this scenario, we investigate the effect of having both of them satisfied. The solution results in 641 handoffs, exactly the same as scenario D where DC1-DC4 are satisfied. Consequently, scenario E is dominated by scenario D.

Table 2 summarizes the results in this section. It shows all cases together with the scenarios we discussed in this section, the number of patient handoffs for each case, and whether each case is *efficient* or not. Those cases that are not dominated by any other case are *efficient* schedules.

As seen in Table 2, scenarios B, C_2, C_4 and D are efficient schedules. However, from a practical standpoint, scenario D is preferred to scenarios C_2 and C_4, since DC1 – DC4 are satisfied with only 1 % increase in the number of patient handoffs. Hence, from practical standpoint, only scenarios B and D are efficient schedules. The only difference between these two schedules is the limit on shift length. Figure 6 shows the resulting schedules corresponding to scenarios B and D (12 h and 16 h shift length limit, respectively).

Fellows at the Mayo MICU are currently working 12-h shifts with shift changes happening at 6 am and 6 pm. Our analysis in this part showed that the current work shift schedule for fellows at Mayo's MICU is indeed optimal if we want to maintain 12-h shifts; however, the 16-h shift length of scenario D is very attractive due to the large number of handoffs saved (190 or 23 % fewer).

3.5 Sensitivity analysis and discussion

In this section, we briefly review the main results from the previous section and then provide further analysis of the shift length constraint.

Day\Time	0-2	2-4	4-6	6-8	8-10	10-12	12-14	14-16	16-18	18-20	20-22	22-24
1 (SAT)	1	1	1	2	2	2	2	2	2	1	1	1
2 (SUN)	1	1	1	2	2	2	2	2	2	3	3	3
3 (MON)	3	3	3	2	2	2	2	2	2	3	3	3
4 (TUE)	3	3	3	1	1	1	1	1	1	2	2	2
5 (WED)	2	2	2	1	1	1	1	1	1	2	2	2
6 (THU)	2	2	2	3	3	3	3	3	3	1	1	1
7 (FRI)	1	1	1	3	3	3	3	3	3	1	1	1
8 (SAT)	1	1	1	2	2	2	2	2	2	3	3	3
9 (SUN)	3	3	3	2	2	2	2	2	2	3	3	3
10 (MON)	3	3	3	1	1	1	1	1	1	2	2	2
11 (TUE)	2	2	2	1	1	1	1	1	1	2	2	2
12 (WED)	2	2	2	3	3	3	3	3	3	1	1	1
13 (THU)	1	1	1	3	3	3	3	3	3	1	1	1
14 (FRI)	1	1	1	2	2	2	2	2	2	3	3	3
15 (SAT)	3	3	3	2	2	2	2	2	2	3	3	3
16 (SUN)	3	3	3	1	1	1	1	1	1	2	2	2
17 (MON)	2	2	2	1	1	1	1	1	1	2	2	2
18 (TUE)	2	2	2	3	3	3	3	3	3	1	1	1
19 (WED)	1	1	1	3	3	3	3	3	3	1	1	1
20 (THU)	1	1	1	2	2	2	2	2	2	3	3	3
21 (FRI)	3	3	3	2	2	2	2	2	2	3	3	3
22 (SAT)	3	3	3	1	1	1	1	1	1	2	2	2
23 (SUN)	2	2	2	1	1	1	1	1	1	2	2	2
24 (MON)	2	2	2	3	3	3	3	3	3	1	1	1
25 (TUE)	1	1	1	3	3	3	3	3	3	1	1	1
26 (WED)	1	1	1	3	3	3	3	3	3	2	2	2
27 (THU)	2	2	2	3	3	3	3	3	3	2	2	2
28 (FRI)	2	2	2	3	3	3	3	3	3	1	1	1
Day\Time	0-2	2-4	4-6	6-8	8-10	10-12	12-14	14-16	16-18	18-20	20-22	22-24

a

Day\Time	0-2	2-4	4-6	6-8	8-10	10-12	12-14	14-16	16-18	18-20	20-22	22-24
1 (SAT)	1	1	1	2	2	2	2	2	2	2	2	3
2 (SUN)	3	3	3	3	3	3	3	2	2	2	2	2
3 (MON)	2	2	2	1	1	1	1	1	1	1	1	2
4 (TUE)	2	2	2	2	2	2	2	3	3	3	3	3
5 (WED)	3	3	3	1	1	1	1	1	1	1	1	3
6 (THU)	3	3	3	3	3	3	3	1	1	1	1	1
7 (FRI)	1	1	1	2	2	2	2	2	2	2	2	1
8 (SAT)	1	1	1	1	1	1	1	2	2	2	2	2
9 (SUN)	2	2	2	3	3	3	3	3	3	3	3	2
10 (MON)	2	2	2	2	2	2	2	3	3	3	3	3
11 (TUE)	3	3	3	1	1	1	1	1	1	1	1	3
12 (WED)	3	3	3	3	3	3	3	1	1	1	1	1
13 (THU)	1	1	1	2	2	2	2	2	2	2	2	1
14 (FRI)	1	1	1	1	1	1	1	3	3	3	3	3
15 (SAT)	3	3	3	2	2	2	2	2	2	2	2	3
16 (SUN)	3	3	3	3	3	3	3	1	1	1	1	1
17 (MON)	1	1	1	2	2	2	2	2	2	2	2	1
18 (TUE)	1	1	1	1	1	1	1	3	3	3	3	3
19 (WED)	3	3	3	2	2	2	2	2	2	2	2	3
20 (THU)	3	3	3	3	3	3	3	1	1	1	1	1
21 (FRI)	1	1	1	2	2	2	2	2	2	2	2	1
22 (SAT)	1	1	1	1	1	1	1	2	2	2	2	2
23 (SUN)	2	2	2	3	3	3	3	3	3	3	3	2
24 (MON)	2	2	2	2	2	2	2	1	1	1	1	1
25 (TUE)	1	1	1	3	3	3	3	3	3	3	3	1
26 (WED)	1	1	1	1	1	1	1	3	3	3	3	3
27 (THU)	3	3	3	2	2	2	2	2	2	2	2	3
28 (FRI)	3	3	3	3	3	3	3	1	1	1	1	1
Day\Time	0-2	2-4	4-6	6-8	8-10	10-12	12-14	14-16	16-18	18-20	20-22	22-24

b

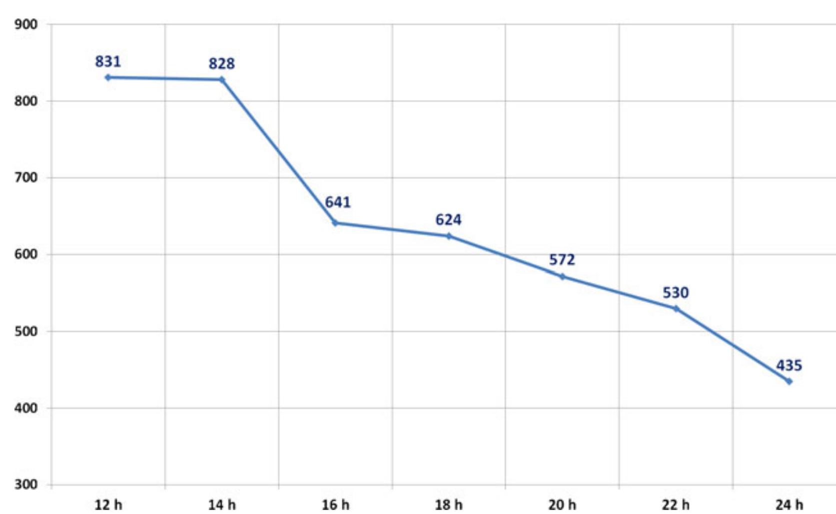
Fig. 6 Resulting schedules with (**a**) 12 h per scenario B and (**b**) Scenario D with 16 h shift length limit. Each number and color refers to one of the three fellows who is assigned to the corresponding time block

The previous section showed that most of the desired constraints can be accommodated without significantly increasing the number of patient handoffs. Those constraints include: no shift change at late night or early morning, at least 1 day off every 7 days, no more than four night shifts in a row and a minimum 1 day off after a run of night shifts. The desired constraint that restricts shift length to 12 h, however, increases the number of patient handoffs by more than 30 %.

Based on ACGME duty-hour regulations, work shifts of residents in PGY-1 must not exceed 16 h while senior trainees (PGY-2 and above residents and all fellows) may be scheduled for a maximum of 24 h of continuous duty. To explore the effect of shift length, we run the model for different shift lengths from 12 h to 24 h (in 2-h increments). We keep all other required and desired constraints active and only change the shift length bound (*ShL* parameter). Figure 7 shows the resulting change in number of patient handoffs.

As seen in Fig. 7, increasing shift length limit results in fewer patient handoffs. The current 12-h shifts in Mayo MICU cause an average of 831 patients to be handed off per month. Should the shift length be extended to 16 h, this will result in nearly a 23 % reduction in number of patient handoffs per month. Increasing the shift length to its maximum allowed limit, i.e. 24 h, results in almost a 48 % reduction in number of patient handoffs per month. On one hand, shorter shifts correlate with more frequent patient handoffs, which potentially results in more

Fig. 7 Number of patient handoffs for different shift length limits



Day\Time	0-2	2-4	4-6	6-8	8-10	10-12	12-14	14-16	16-18	18-20	20-22	22-24
1 (SAT)	1	1	1	1	1	1	1	3	3	3	3	3
2 (SUN)	3	3	3	2	2	2	2	2	2	2	2	1
3 (MON)	1	1	1	1	1	1	1	2	2	2	2	2
4 (TUE)	2	2	2	3	3	3	3	3	3	3	3	2
5 (WED)	2	2	2	2	2	2	2	3	3	3	3	3
6 (THU)	3	3	3	1	1	1	1	1	1	1	1	3
7 (FRI)	3	3	3	3	3	3	3	1	1	1	1	1
8 (SAT)	1	1	1	2	2	2	2	2	2	2	2	1
9 (SUN)	1	1	1	1	1	1	1	2	2	2	2	2
10 (MON)	2	2	2	3	3	3	3	3	3	3	3	2
11 (TUE)	2	2	2	2	2	2	2	3	3	3	3	3
12 (WED)	3	3	3	1	1	1	1	1	1	1	1	3
13 (THU)	3	3	3	3	3	3	3	2	2	2	2	2
14 (FRI)	2	2	2	1	1	1	1	1	1	1	1	2
15 (SAT)	2	2	2	2	2	2	2	1	1	1	1	1
16 (SUN)	1	1	1	3	3	3	3	3	3	3	3	1
17 (MON)	1	1	1	1	1	1	1	2	2	2	2	2
18 (TUE)	2	2	2	3	3	3	3	3	3	3	3	2
19 (WED)	2	2	2	2	2	2	2	3	3	3	3	3
20 (THU)	3	3	3	1	1	1	1	1	1	1	1	3
21 (FRI)	3	3	3	3	3	3	3	2	2	2	2	2
22 (SAT)	2	2	2	1	1	1	1	1	1	1	1	2
23 (SUN)	2	2	2	2	2	2	2	1	1	1	1	1
24 (MON)	1	1	1	3	3	3	3	3	3	3	3	1
25 (TUE)	1	1	1	1	1	1	1	3	3	3	3	3
26 (WED)	3	3	3	2	2	2	2	2	2	2	2	3
27 (THU)	3	3	3	3	3	3	3	1	1	1	1	1
28 (FRI)	1	1	1	2	2	2	2	2	2	2	2	1
Day\Time	0-2	2-4	4-6	6-8	8-10	10-12	12-14	14-16	16-18	18-20	20-22	22-24

Average Duty-hours	1.Geen Fellow: 56 hrs/wk 2.Red Fellow: 56 hrs/wk 3.Yellow Fellow: 56 hrs/wk
# Night Shifts	1.Geen Fellow: 9 2.Red Fellow: 10 3.Yellow Fellow: 9
# Days Off	1.Geen Fellow: 6 2.Red Fellow: 7 3.Yellow Fellow: 7

Fig. 8 Equitable schedule with all required and desired constraints and 16-h shift length limits

medical errors due to communication breakdown and loss of information during the handoff process. On the other hand, longer shifts are associated with extreme tiredness and sleep deprivation which can also contribute to fatigue-related medical errors.

A reasonable tradeoff between fatigue and handoffs should be established to minimize medical errors and achieve the best patient outcomes. However, to date there is no solid methodology to quantify physicians' fatigue and the effect of fatigue on quality of care and patient outcomes. The best we could do was to collect expert opinions. Several program directors and physicians that we have interviewed believe that 24-h shifts are acceptable and worth the benefit of fewer patient handoffs. A majority of program directors, chief residents and fellows believe 16-h shifts are very reasonable and worth the benefit of the 20 %–25 % reduction in patient handoffs (compared to 12-h shifts). The 16-h shift length limit is permitted by ACGME and could be applied to different trainee levels (i.e. PGY-1 residents, senior (PGY-2 and above) residents, and fellows). This appears to provide a good tradeoff between the adverse effects of physicians' fatigue and the adverse effects of more frequent patient handoffs.

One final point is the importance of maintaining fairness and balance among the trainees' schedules. While this is not a mandated requirement, it is clearly important for implementation and trainee morale. Therefore, we added measures and associated constraints to ensure balance among the schedules for average duty hours, number of night shifts, and the number of days off. Figure 8 shows the resulting equitable schedule and associated "fairness" values that yields the same 641 patient handoffs (with the shift length limit set at 16 h).

4 Future work

There are several directions for future research. First, it is not currently known how much the extra weariness due to longer shifts contributes to fatigue-related medical errors. If physician fatigue and its effect on medical errors can be quantified in a systematic way, it will help in scientifically evaluating schedules that minimize the number of patient handoffs. Second, the connection between ICU rounding time and patient census pattern could be further investigated. In this study, we included a required constraint to keep bedside rounds at the current time to avoid the complex effect of rounding time on the patient discharge process, which directly influences ICU patient census.

5 Conclusions

In this paper, we developed a new patient-centered model for scheduling residents and fellows (trainees) to minimize number of patient handoffs, which have been linked with medical errors caused by communication breakdowns and adverse events. While previous literature focuses on the logistics of the handoff, we bring a new systems perspective to this problem by designing schedules that minimize the number of patients that are handed off, thereby reducing the opportunity for serious error. Our integer programming model designs work shifts such that all ACGME duty-hour regulations are satisfied, required coverage is achieved, livability rules are met, and patient handoffs are minimized. The general form of our model presented in Section 2 can be used by any healthcare operation that wants to reduce patient handoffs and that has duty-hour restrictions and similar livability constraints. Should the size of the model render the problem intractable for other healthcare units, heuristics approaches such as the Tabu Search can be employed to solve the integer program (see, for example, [51] and [52]).

In a case study of a Medical Intensive Care Unit (MICU) at an academic medical center (the Mayo Clinic in Rochester, Minnesota) we demonstrated how our model could be applied to reduce the number of patient handoffs. We found that most desired constraints (livability rules) can be satisfied with a negligible increase in number of patient handoffs. The desired constraint that had the largest impact on handoffs was the shift length. By increasing the shift length from 12 to 16 h it was possible to reduce handoffs by 23 % relative to the current MICU schedule. 24-h shifts (the maximum allowable shift length) resulted in a 48 % reduction in the number of patient handoffs. It is worth noting that in the proposed schedule no new trainees (fellow for the case study of Mayo MICU) need to be added beyond the minimum number needed to provide the required coverage specified by required constraint #6 (RC6), i.e. Eq. 10 (required coverage is 24/7 for the case study). Therefore, in terms of financial costs, the as-is schedule and the proposed schedules are exactly the same.

Based on discussions with staff at Mayo Clinic, we found that 16-h shifts provided a reasonable tradeoff between medical errors due to trainee fatigue and medical errors due to communication breakdowns as a result of more frequent patient handoffs. The new shift design approach discussed in this paper is under consideration for implementation at Mayo Clinic. A shift assignment approach based on the work discussed in this paper was accepted by the practice and additional services are considering the use of the general methodology to assist in staff scheduling at Mayo Clinic.

Acknowledgments This work was funded in part by the Center for the Science of Health Care Delivery at Mayo Clinic, Rochester, Minnesota, and by NSF grant CMMI-1068638. The authors would like to thank all program directors and coordinators, consultants, fellows and residents at Mayo Clinic for their insightful comments and feedback. In addition, we acknowledge the contributions of Bjorn Berg, Dr. Jeanne Huddleston, Todd Huschka, Dr. Anil Patel, and Dr. Christopher Janish who provided data analysis, modeling expertise, and practice knowledge.

References

1. Kohn LT, Corrigan J, Donaldson MS, Institute of Medicine (U.S.). Committee on Quality of Health Care in America (1999) To err is human building a safer health system
2. Volpp KG, Grande D (2003) Residents' suggestions for reducing errors in teaching hospitals. N Engl J Med 348(9):851–855. doi:10.1056/NEJMsb021667
3. Leape LL, Swankin DS, Yessian MR (1999) A conversation on medical injury. Public Health Rep 114(4):302–317
4. Institute of Medicine (U.S.). Committee on Quality of Health Care in America (2001) Crossing the quality chasm: a new health system for the 21st century. National Academy Press, Washington, D.C
5. Institute of Medicine (U.S.). Committee on Optimizing Graduate Medical Trainee (Resident) Hours and Work Schedules to Improve Patient Safety, Ulmer C, Wolman DM, Johns MME (2009) Resident duty hours: enhancing sleep, supervision, and safety. National Academies Press, Washington, D.C
6. Nasca TJ, Day SH, Amis ES Jr (2010) The new recommendations on duty hours from the ACGME Task Force. N Engl J Med 363(2):e3. doi:10.1056/NEJMsb1005800
7. Duty Hours: ACGME Standards (Effective July 2011). Available at: http://www.acgme.org/acgmeweb/GraduateMedicalEducation/DutyHours.aspx
8. Vidyarthi AR, Arora V, Schnipper JL, Wall SD, Wachter RM (2006) Managing discontinuity in academic medical centers: strategies for a safe and effective resident sign-out. J Hosp Med 1(4):257–266. doi:10.1002/jhm.103
9. Horwitz LI, Krumholz HM, Green ML, Huot SJ (2006) Transfers of patient care between house staff on internal medicine wards: a national survey. Arch Intern Med 166(11):1173–1177. doi:10.1001/archinte.166.11.1173
10. Philibert I, Leach DC (2005) Re-framing continuity of care for this century. Qual Saf Health Care 14(6):394–396. doi:10.1136/qshc.2005.016170
11. Horwitz LI, Moin T, Green ML (2007) Development and implementation of an oral sign-out skills curriculum. J Gen Intern Med 22(10):1470–1474. doi:10.1007/s11606-007-0331-0
12. Hutter MM, Kellogg KC, Ferguson CM, Abbott WM, Warshaw AL (2006) The impact of the 80-h resident workweek on surgical residents and attending surgeons. Ann Surg 243(6):864–871. doi:10.1097/01.sla.0000220042.48310.66, discussion 871–865
13. Lockley SW, Landrigan CP, Barger LK, Czeisler CA (2006) When policy meets physiology: the challenge of reducing resident work hours. Clin Orthop Relat Res 449:116–127. doi:10.1097/01.blo.0000224057.32367.84
14. Patterson ES, Wears RL (2010) Patient handoffs: standardized and reliable measurement tools remain elusive. Jt Comm J Qual Patient Saf 36(2):52–61
15. Risser DT, Rice MM, Salisbury ML, Simon R, Jay GD, Berns SD (1999) The potential for improved teamwork to reduce medical

errors in the emergency department. The MedTeams Research Consortium. Ann Emerg Med 34(3):373–383
16. Sutcliffe KM, Lewton E, Rosenthal MM (2004) Communication failures: an insidious contributor to medical mishaps. Acad Med 79(2):186–194
17. Arora V, Kao J, Lovinger D, Seiden SC, Meltzer D (2007) Medication discrepancies in resident sign-outs and their potential to harm. J Gen Intern Med 22(12):1751–1755. doi:10.1007/s11606-007-0415-x
18. Frankel HL, Foley A, Norway C, Kaplan L (2006) Amelioration of increased intensive care unit service readmission rate after implementation of work-hour restrictions. J Trauma 61(1):116–121. doi:10.1097/01.ta.0000222579.48194.2b
19. Jagsi R, Kitch BT, Weinstein DF, Campbell EG, Hutter M, Weissman JS (2005) Residents report on adverse events and their causes. Arch Intern Med 165(22):2607–2613. doi:10.1001/archinte.165.22.2607
20. Greenberg CC, Regenbogen SE, Studdert DM, Lipsitz SR, Rogers SO, Zinner MJ, Gawande AA (2007) Patterns of communication breakdowns resulting in injury to surgical patients. J Am Coll Surg 204(4):533–540. doi:10.1016/j.jamcollsurg.2007.01.010
21. Landrigan CP, Rothschild JM, Cronin JW, Kaushal R, Burdick E, Katz JT, Lilly CM, Stone PH, Lockley SW, Bates DW, Czeisler CA (2004) Effect of reducing interns' work hours on serious medical errors in intensive care units. N Engl J Med 351(18):1838–1848. doi:10.1056/NEJMoa041406
22. Petersen LA, Brennan TA, O'Neil AC, Cook EF, Lee TH (1994) Does housestaff discontinuity of care increase the risk for preventable adverse events? Ann Intern Med 121(11):866–872
23. Li P, Stelfox HT, Ghali WA (2011) A prospective observational study of physician handoff for intensive-care-unit-to-ward patient transfers. Am J Med 124(9):860–867. doi:10.1016/j.amjmed.2011.04.027
24. Kitch BT, Cooper JB, Zapol WM, Marder JE, Karson A, Hutter M, Campbell EG (2008) Handoffs causing patient harm: a survey of medical and surgical house staff. Jt Comm J Qual Patient Saf 34(10):563–570
25. Gandhi TK (2005) Fumbled handoffs: one dropped ball after another. Ann Intern Med 142(5):352–358
26. Sexton A, Chan C, Elliott M, Stuart J, Jayasuriya R, Crookes P (2004) Nursing handovers: do we really need them? J Nurs Manag 12(1):37–42
27. Ye K, Mc DTD, Knott JC, Dent A, MacBean CE (2007) Handover in the emergency department: deficiencies and adverse effects. Emerg Med Australas 19(5):433–441. doi:10.1111/j.1742-6723.2007.00984.x
28. Arora V, Johnson J (2006) A model for building a standardized hand-off protocol. Jt Comm J Qual Patient Saf 32(11):646–655
29. Solet DJ, Norvell JM, Rutan GH, Frankel RM (2005) Lost in translation: challenges and opportunities in physician-to-physician communication during patient handoffs. Acad Med 80(12):1094–1099
30. Solet DJ, Norvell JM, Rutan GH, Frankel RM (2004) Physician-to-physician communication: methods, practice and misgivings with patient handoffs. J Gen Intern Med 19:108
31. Nemeth CP (2008) Improving healthcare team communication: building on lessons from aviation and aerospace. Ashgate, Aldershot
32. Arora V, Johnson J, Lovinger D, Humphrey HJ, Meltzer DO (2005) Communication failures in patient sign-out and suggestions for improvement: a critical incident analysis. Qual Saf Health Care 14(6):401–407. doi:10.1136/qshc.2005.015107
33. Arora VM, Johnson JK, Meltzer DO, Humphrey HJ (2008) A theoretical framework and competency-based approach to improving handoffs. Qual Saf Health Care 17(1):11–14. doi:10.1136/qshc.2006.018952
34. Mistry KP, Jaggers J, Lodge AJ, Alton M, Mericle JM, Frush KS, Meliones JN (2008) Using six sigma(R) methodology to improve handoff communication in high-risk patients. In: Henriksen K, Battles JB, Keyes MA, Grady ML (eds) Advances in patient safety: New directions and alternative approaches (Vol. 3: Performance and tools). Advances in Patient Safety, Rockville
35. Cheung DS, Kelly JJ, Beach C, Berkeley RP, Bitterman RA, Broida RI, Dalsey WC, Farley HL, Fuller DC, Garvey DJ, Klauer KM, McCullough LB, Patterson ES, Pham JC, Phelan MP, Pines JM, Schenkel SM, Tomolo A, Turbiak TW, Vozenilek JA, Wears RL, White ML (2010) Improving handoffs in the emergency department. Ann Emerg Med 55(2):171–180. doi:10.1016/j.annemergmed.2009.07.016
36. Donchin Y, Gopher D, Olin M, Badihi Y, Biesky M, Sprung CL, Pizov R, Cotev S (2003) A look into the nature and causes of human errors in the intensive care unit. 1995. Qual Saf Health Care 12(2):143–147, discussion 147–148
37. Kemp CD, Bath JM, Berger J, Bergsman A, Ellison T, Emery K, Garonzik-Wang J, Hui-Chou HG, Mayo SC, Serrano OK, Shridharani S, Zuberi K, Lipsett PA, Freischlag JA (2008) The top 10 list for a safe and effective sign-out. Arch Surg 143(10):1008–1010. doi:10.1001/archsurg.143.10.1008
38. Clark CJ, Sindell SL, Koehler RP (2011) Template for success: using a resident-designed sign-out template in the handover of patient care. J Surg Educ 68(1):52–57. doi:10.1016/j.jsurg.2010.09.001
39. Abraham J, Kannampallil TG, Patel VL (2012) Bridging gaps in handoffs: a continuity of care based approach. J Biomed Inform 45(2):240–254. doi:10.1016/j.jbi.2011.10.011
40. Borman KR, Jones AT, Shea JA (2012) Duty hours, quality of care, and patient safety: general surgery resident perceptions. J Am Coll Surg 215(1):70–77. doi:10.1016/j.jamcollsurg.2012.02.010
41. Carter MW, Lapierre SD (2001) Scheduling emergency room physicians. Health Care Manag Sci 4(4):347–360
42. Ernst AT, Jiang H, Krishnamoorthy M, Sier D (2004) Staff scheduling and rostering: a review of applications, methods and models. Eur J Oper Res 153(1):3–27. doi:10.1016/S0377-2217(03)00095-X
43. Aickelin U, Dowsland KA (2004) An indirect genetic algorithm for a nurse-scheduling problem. Comput Oper Res 31(5):761–778. doi:10.1016/S0305-0548(03)00034-0
44. Gutjahr WJ, Rauner MS (2007) An ACO algorithm for a dynamic regional nurse-scheduling problem in Austria. Comput Oper Res 34(3):642–666. doi:10.1016/j.cor.2005.03.018
45. Gendreau M, Ferland J, Gendron B, Hail N, Jaumard B, Lapierre S, Pesant G, Soriano P (2007) Physician scheduling in emergency rooms. Pract Theory Autom Timetabling Vi 3867:53–66
46. Gascon V, Villeneuve S, Michelon P, Ferland JA (2000) Scheduling the flying squad nurses of a hospital using a multi-objective programming model. Ann Oper Res 96:149–166
47. Bard JF, Purnomo HW (2005) Short-term nurse scheduling in response to daily fluctuations in supply and demand. Health Care Manag Sci 8(4):315–324
48. Beaulieu H, Ferland JA, Gendron B, Michelon P (2000) A mathematical programming approach for scheduling physicians in the emergency room. Health Care Manag Sci 3(3):193–200
49. Sherali HD, Ramahi MH, Saifee QJ (2002) Hospital resident scheduling problem. Prod Plan Control 13(2):220–233
50. Cohn A, Root S, Kymissis C, Esses J, Westmoreland N (2009) Scheduling medical residents at Boston University School of Medicine. Interfaces 39(3):186–195. doi:10.1287/inte.1080.0369
51. Balas E, Martin CH (1980) Pivot and complement–a heuristic for 0–1 programming. Manag Sci 26(1):86–96
52. Lokketangen A, Glover F (1998) Solving zero–one mixed integer programming problems using tabu search. Eur J Oper Res 106(2–3):624–658