ABSTRACT

Under common medication schedules, all hospital inpatients receive their scheduled medications at the same time. However, nearly 20% of all inpatients over age 40 have COPD and require inhaled medications that take ~20 minutes to administer. As a result, inhaled medications are often administered late. To level clinician workload and reduce tardiness, we use a two-stage stochastic program to select staggered administration schedules for inhaled drugs. Guided by critical ratio priorities, a team of clinicians travels from care unit to care unit treating patients, effectively pooling random demand streams and serendipitously supporting a primary care treatment model for COPD patients.

KEYWORDS: Health Care Quality, Scheduling Policies & Systems, Stochastic Programming

INTRODUCTION

Some drugs must be administered to hospital patients at regular intervals to maintain their effectiveness. To help ensure safe, timely administration of those medications, hospital pharmacies and clinicians use standard, hospital-wide medication schedules (CMS, 2011). Unfortunately, many patients continue to experience adverse drug reactions or medication errors during their stay in the hospital (Lucado et al., 2011). The most common are “wrong time” errors (Balas et al., 2004; Keers, et al. 2013), which occur when medications aren’t administered within 30-60 minutes of the time scheduled (ISMP, 2011). A disproportionate fraction of all wrong time medication errors involve respiratory therapy (RT) drugs (Sakowski et al., 2005), which are prescribed for patients with breathing ailments like Chronic Obstructive Pulmonary Disorder (COPD). Nearly 20% of all hospital patients aged 40 or older have COPD as a primary diagnosis or a complicating factor (Wier et al., 2011).

One reason for the high incidence of late medications is that RT drugs are often inhaled rather than administered orally or by injection, a process requiring between nine and twenty minutes per treatment (AARC, 2011). To maintain therapeutic levels, those drugs must be re-administered at regular intervals of between two and twelve hours. Although newer, longer-acting inhaled medications have been approved for use in the US, many physicians still prescribe inhaled RT medications that are administered three (TID, the dosing frequency assumed for our study) or four (QID) times per day. With common medication times, all TID prescriptions throughout the hospital are due at the same time. Thus, Respiratory Care Practitioners (RCPs) face significant scheduled workload peaks several times per day. Ford (2011) argued that RCP staffing levels based on the aggregate workload for a shift are rarely
sufficient to complete all scheduled RT medications on time. In some hospitals, 75 percent of the scheduled RT workload is tardy (Chatburn, Gole et al, 2011).

Clinical evidence indicates that adherence to prescribed medication times is essential for the effective management and control of disease symptoms (Restrepo, et al., 2008). Failure to do so can exacerbate those symptoms and has been associated with increased length-of-stay (Bates et al., 1997; Classen et al., 1997) and premature re-admission to the hospital (Greenwald et al., 2007). Such outcomes increase unreimbursed costs for hospitals and reduce their revenues (AARC, 2011). One obvious way to improve on-time RT medication rates and avoid these problems is to increase RCP staffing levels so there is enough capacity to administer all scheduled medications on time. However, this may leave RCPs underutilized at times other than scheduled medication times. Sakowski et al., (2005) suggested a more cost-effective strategy: “stagger” scheduled medication times for RT patients or for each care unit in a way that attenuates workload peaks for RCPs. Because hospital pharmacies deem it impractical to implement staggered scheduled medication times for individual RT patients, this research focuses on medication schedules for RT patients that vary by the care unit where they are being treated.

The staggered medication times for the different care units must conform to optimal RT patient management and must also be coordinated with the scheduled routines of other clinical and support units within the hospital. These concerns limit the set of medication times that can be used to level RCP workload and make it difficult to alter them once new medication times are established. In addition, to ensure that all scheduled RT treatments have a good chance of being administered at the staggered medication times, changes to RCP work schedules may be required (Chatburn et al., 2011). Ideally, RCP work scheduling decisions are driven by accurate estimates of temporal workload that are based on forecasts of RT patient census and the timing of events like scheduled medication times. However, patients with breathing disorders like COPD are often admitted to the hospital with co-morbidities such as pneumonia, coronary heart disease, hypertension, or diabetes, and as a result, can be found in several different care units throughout the hospital. Because the RT patient census in each department tends to vary from day to day, it can be difficult to accurately predict clinician workload and staffing requirements.

Cowles et al. (2007, 36-37) found that RCPs are usually assigned to one or two care units. To better leverage the advantages of staggered medication times, we propose that most RCPs move together as a team from care unit to care unit administering medications. This effectively pools the separate demand streams across multiple care units, reducing relative variation and improving forecast accuracy. Because most RCPs visit most care units at least once each shift, this strategy also supports a primary care model for patients, which has been shown to provide improved medical outcomes for COPD patients (Meulepas et al., 2007) and reduced rates of premature re-admissions.

In this study, we model the selection of staggered medication times as a two-stage stochastic program. In the first stage, we establish scheduled medication times for subsets of care units that result in the minimum number of late treatments with exogenous RCP staffing levels and patient census in each subset at the 90%ile. After solving the deterministic first stage, we obtain the expectation of late treatments for the selected medication times by repeated simulating RT patient census for the care units and allocating the available RCPs to minimize late treatments. Compared with common medication schedules, our simulation results revealed the potential for a 96% reduction in the expected number of late medications per day (from an average of 46 to 1.7). However, these promising results address only one of the uncertainties affecting on-time performance.
By the beginning of each shift, most of the uncertainty about RT patient census for the next few hours has been resolved so the RCPs reporting for duty can be matched with patients and plans for addressing any apparent demand-supply mismatches can be developed. As the shift progresses, however, RCPs inevitably find that some patients are eating, or out of their room for tests when they arrive to administer a scheduled medication, or that they are delayed in starting their next treatment because they are addressing an emergency with another patient. These largely uncontrollable stochastic events that occur within the populations of RT inpatients and RCPs suggest the need for a real-time control mechanism to (re-) prioritize patients and dispatch RCPs. We propose a real-time dispatching algorithm based on critical ratios to dynamically re-deploy RCPs as these stochastic events unfold. Its performance is reviewed in another version of this paper.

The remainder of our paper is organized as follows. In section 2 we review the key operational features of this complex operational environment, describe the clinical and economic incentives for improving on-time medication administration, and review alternative ways to achieve those outcomes. In section 3 we model the selection of staggered medication times as a two stage stochastic program and discuss our real-time dispatching system. In section 4, we present the results of a computational study based on hospital pharmacy data that compares on-time medication performance under common medication and staggered medication times. In the last section, we summarize our findings, identify some of the limitations of our approach, and identify a few opportunities for further study.

LITERATURE REVIEW

In this section, we review the economic incentives offered to hospitals for improving health care outcomes, with a particular focus on the incidence & costs of wrong time errors for RT medications. We review strategies to improve on-time administration for RT drugs and introduce the key operational issues associated with staggered medication schedules: uncertain demand and capacity; medical and operational constraints that limit schedule flexibility; staffing and scheduling implications for clinicians; and real-time dispatching of RCPs in response to uncertain patient demand and clinician capacity.

Economic incentives for on-time treatments

As one of the nation’s largest health care insurers, the U.S. government oversees several high-impact initiatives that are intended to improve medical outcomes for patients while reducing unnecessary spending by providers. For example, under its inpatient prospective payment system (iPPS), Medicare payments to hospitals are based on the patient’s diagnosis and illness severity rather than the total cost of the services consumed while treating the patient. Under the Hospital Readmissions Reduction Program (HRRP), the proportion of patients who are readmitted within 30 days of discharge is used as a proxy for a hospital’s quality of care. The program reduces iPPS payments to those hospitals with above the risk-adjusted nationwide mean readmission rates for certain types of illnesses such as acute myocardial infarction (heart attack), congestive heart failure, pneumonia, and beginning FY 2014, COPD and elective knee or hip replacement.

Despite these initiatives, there is widespread agreement that the quality of health care received by many patients is still far from ideal (Kelley, et al., 2005). Lucado et al. (2011) report that 4.7% of all hospital in-patients experience an adverse drug event or medication error during their stay, but other studies suggest the incidence of medication errors may be 4 times that rate (Barker, et al., 2002). The Center for Medicare and Medicaid Services (CMS) considers a
Medication error to be “any preventable event that may cause or lead to inappropriate medication use or patient harm while the medication is in the control of the health care professional, patient or consumer. Such events may be related to professional practice, health care products, procedures, and systems, including prescribing; order communication; product labeling, packaging, and nomenclature; compounding; dispensing; distribution; administration; education; monitoring; and use” (Martin, 2011). Adverse drug events, on the other hand, are injuries caused by the use of a medication. They include both adverse drug reactions (“an effect which is noxious and unintended, and which occurs at doses used in man for prophylaxis, diagnosis or therapy,” as well as harmful effects arising from errors at any medication use stage including ordering, transcribing, dispensing, administering or monitoring of a drug (Aljadhey et al., 2013). After controlling for other factors, Classen et al., (1997) attributed adverse drug events to a 1.91 day increase in the average length of stay for affected patients. Thus in addition to placing patients at risk, medication errors and adverse drug events increase the likelihood of unreimbursed costs for hospitals under iPPS.

Although clinical evidence suggests that adherence to prescribed medications and dosing times is essential to the management and control of symptoms (Restrepo, et al., 2008), the most common medication errors – about 1 of every 3 -- are "wrong time" errors (Balas et al., 2004; Keers, et al., 2013). Wrong time medication errors occur when medications are not administered within 30 or 60 minutes of the scheduled time (ISMP, 2011). Sakowski et al. (2005) found that a disproportionate fraction of the wrong-time medication errors in the acute care hospitals they examined involved drugs used for respiratory therapy (RT). These drugs are often prescribed for patients with a primary or contributing diagnosis of COPD, who account for about 20% of all adult hospital patients aged 40 or more (Weir et al., 2011).

Patients with chronic respiratory diseases also tend to have the highest rate of premature readmissions (Alonso et al., 2001; Jencks et al., 2009). Failing to adhere to scheduled medication times inside the hospital may set a poor example for respiratory patients who are expected to administer their own treatments after discharge, contributing to disease exacerbations and premature readmissions following discharge. For example, Greenwald et al. (2007) found that the lack of patient adherence to the medications prescribed at discharge is a key driver of post-discharge adverse drug events and that avoidable hospital readmissions are often linked to post-discharge adverse drug events, especially among older patients. Jack et al. (2009) found that patients who are educated to identify the correct medicines and have formulated concrete plans to obtain and administer drugs after discharge are 30% less likely to suffer a premature readmission. Finally, Alonso et al. (2001) found that the annual hospital readmission rate for COPD patients who reported good adherence to their prescribed medication schedules was barely half that of COPD patients with poor adherence.

Timely administration of respiratory therapy medications in acute care hospitals

In most hospitals, the process of administering prescribed medications is complex, involving many discrete steps and checks by several different members of the health care team. To maintain medications at therapeutic levels, for example, some drugs must be administered to hospital patients at regular intervals (e.g., TID, or three times a day during waking hours). To help ensure safe, timely administration of those medications, the pharmacy departments and clinicians in most hospitals are encouraged to adhere to standard, hospital-wide medication schedules for drugs that are administered on a repeating cycle such as once a day, BID (twice a day), TID (three times a day), hourly intervals (every 1, 2, 3 or more hours), etc. (CMS, 2011). Under hospital-wide standard medication schedules, all patients in the hospital with
prescriptions that are to be administered TID are scheduled to receive those medications at the same times – say 09:00, 13:00, and 17:00.

Unfortunately, standard medication schedules tend to create significant workload peaks for RCPs. Many RT drugs are inhaled rather than swallowed or injected, and patients typically need between nine and twenty minutes to inhale their medications (Ari et al., 2009; AARC, 2011). The delivery devices (dry powder inhalers, metered dose inhalers, or nebulizers) usually require special skills to operate and because the drugs have potentially serious side effects, RCPs must remain at the patient’s bedside to monitor treatment progress. Allowing time to review and update the patient’s record, to retrieve medications and prepare them for delivery, to coordinate with other providers and perform common but unscheduled RT procedures, we found that RCPs can complete about two nebulized RT treatments per hour, comparable to industry standards (AARC, 2012).

To illustrate the staffing implications of a common medication schedule, suppose there are 40 RT in-patients in a hospital’s Medical-Surgical departments who are scheduled to receive their TID RT medications at 09:00, 13:00, and 17:00. Further suppose that it takes 30 minutes to administer an aerosolized drug to a patient, and because patients may have an adverse reaction to those drugs, the RCP must remain with the patient while the drug is administered. Finally, note that the Institute for Safe Medical Practices (ISMP, 2011) allows RT drugs administered within 60 minutes of their scheduled times to be considered “on time.” In Table 1, we show that all 40 scheduled medications due at 9:00 may be considered on time as long as least eight treatments are administered during each of the five ½ hour intervals centered on 9:00. The hospital would need 8 RCPs working non-stop and in parallel to accomplish this, or about 1 RCP for every 5 RT patients.

<table>
<thead>
<tr>
<th>30 minute time block beginning</th>
<th>8:00</th>
<th>8:30</th>
<th>9:00</th>
<th>9:30</th>
<th>10:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of scheduled RT Treatments</td>
<td></td>
<td></td>
<td>40</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum RT clinicians needed to complete all treatments w/in 60 min of scheduled time</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
</tr>
</tbody>
</table>

Chatburn et al. (2011) recently reported that in one hospital they studied, the available clinicians were only able to complete 25 percent of the scheduled RT treatments. Some states have attempted to remediate this problem by establishing minimum safe staffing levels for respiratory care clinicians. For example, a proposed amendment to California’s Health and Safety Code (Section 1276.45 a[6]) calls for RCP staffing ratios of one clinician for every 10 RT patients in medical and surgical departments. However, based on the simple example above, that ratio would provide only half the staff needed to complete all forty 09:00 scheduled treatments within the allowed time window.

**Strategies to reduce wrong-time medication errors with RT patients**

Sakowski et al. (2005) suggested that “staggering” the scheduled medication times for RT patients could more evenly distribute the clinician workload over the course of a day. However, staggering medication times for RT patients can also introduce a number of new operational complexities. For example, to maintain prescribed medications at therapeutic levels over a period of time, many drugs must be re-administered periodically. Standardized medication schedules help prioritize pharmacy and nursing activities and help ensure safe and timely
medication administration. Thus by staggering the standard medication times for certain types of patients, the effectiveness of a hospital-wide common dosing plan may be compromised. Furthermore, medication administration is only one of many different hospital routines that the medical team responsible for treating the patient must complete each day. For example, patient blood draws and vital signs are usually taken early in the morning, followed by physician rounds and frequently, more tests or diagnostic imaging. Thus staggered RT dosing times should be prioritized and coordinated with other routine patient services to avoid interference or unnecessary delay.

On-time medication performance largely depends on having enough RCPs available to administer the medication at the time they are scheduled. Staggering scheduled medication times for RT patients alters temporal workload patterns, and may require different RCP therapist work schedules to ensure that is enough capacity to all scheduled treatments on time. Finally, hospitals operate 24 hrs/day, seven days/week so periodically, patient care must be transferred from one set of providers to another. Effective handoff practices (ie, mechanisms for transferring information, responsibility and authority) are regarded as critical to continuity of care and patient safety (Haque, 2010). To ensure adequate time to safely complete those handoffs, they are usually planned for a period of about 30 minutes around the time of each shift change. During those times, clinicians are involved in handoffs and are not available to administer RT treatments.

Although staggered medication schedules can reduce demand peaks for RCPs, the number of RT inpatients requiring those treatments must be considered a random variable. For example, among patients diagnosed with COPD, the winter months tend to bring more frequent exacerbations and increased rates of hospitalization (Donaldson et al., 2012). The times that patients are actually available for treatments are also subject to uncertainty. For example, following patient rounds, physicians may request additional tests or diagnostic imaging for some patients. Not all RCP work is pre-planned, and unscheduled tasks (i.e., spontaneous, often high-priority demands for clinician skills) often inhibit the ability of clinicians to complete all scheduled RT treatments on time. For example, Chatburn et al. (2011) found that on average, unscheduled work at their institution accounted for an average 45% of RCP workload. This uncertainty complicates most aspects of scheduling treatments and planning RCP staffing needs.

Research Objectives

In this study, we focus on establishing medication schedules and deploying clinical staff to improve on-time drug administration performance among RT patients. Our strategy is based on staggered medication schedules for RT drugs across care units, with clinicians moving together as a team from unit to unit. We envision a hierarchy of interrelated decisions: (1) establishing the best time for scheduled treatments in each care unit; (2) developing clinician work schedules a fortnight or more in advance that provide a high probability the scheduled treatments are completed on time; (3) planning the administration of scheduled medications at the beginning of each shift; and (4) dispatching clinicians over the course of the shift, adjusting priorities in real time as the administration schedule is disrupted by environmental uncertainties.

STAGGERED MEDICATION SCHEDULES AND CLINICIAN DISPATCHING

Staggered medication schedules for inhaled drugs can help improve on-time administration performance. Like Chatburn et al. (2011), we establish different RT medication times for subsets of care units. However, although some care units require an RCP on the floor at all
times, and in many hospitals RCPs work in just one or two care units (Cowles et al., 2007), our strategy allows most RCPs to move as a team from care unit to unit treating RT patients. Because each RCP visits most of the care units in the hospital each shift, this enables a “primary care” treatment model that often results in better outcomes for patients. Serendipitously, it also has the effect of “pooling” demand for inhaled medications across multiple care units, enabling the team of RCPs to better respond to demand variability.

RT drugs are frequently administered three times per day during waking hours (TID), so it is important that the staggered medication times for each care unit occur at intervals that maintain therapeutic effectiveness. In addition, scheduled medication times should not interfere with other routine but high-priority processes such as doctors’ rounds or patient handoffs between shifts. The temporal workload for RCPs is largely influenced by the number of RT patients in each care unit, which we regard as independent random variables, and the scheduled medication times selected for each of those unit. To achieve a high probability that all scheduled medications are administered on time, the selected medication times should be based on clinician capacity and the probability distribution for the number of RT patients in each care unit.

One approach is to evaluate both medication timing and RCP staffing level decisions simultaneously. Because these decisions interact to influence the objective value, the resulting non-linear program may prove difficult to solve. An alternative is to model the medication time problem as a two-stage stochastic program with exogenous RCP staffing levels, where a staggered medication time is chosen for each care unit or combination of care units in the deterministic first stage. In the stochastic second stage, we simulate RT patient census for the subsets of care unit assigned to each scheduled medication time and deploy the available RCPs to minimize late treatments to obtain a probability distribution for late treatments for the chosen medication times. We should consider assigning more than one care unit to the same medication times because the standard deviation of the convolved patient census distribution for the combined care units tend to be less than the sum of the individual care unit standard deviations. That is, it may be possible to achieve the same level of service with fewer resources when care units are pooled in this fashion.

There is one other noteworthy characteristic of the medication timing problem. We assume that RCPs will typically visit each care unit in order of its scheduled medication time. If the number of scheduled treatments in a particular unit is unusually high, however, RCPs may have to delay starting scheduled treatments in subsequent units by as much as one hour, the allowable time window for on-time treatments suggested by with American Association for Respiratory Care (AARC, 2011). For this reason, we view the scheduled medication times and the times we plan to actually administer the scheduled medications to be distinct. The planned medication administration times (variables Y_tj in this model) are recourse variables that may change once the actual RT patient census other uncertainties are revealed. The staggered medication time schedule problem we present next relies on the following notation.

**Notation for the Staggered Medication Time Schedule Problem**

**Parameters**

D The number of different hospital care units treating RT patients, indexed d=1,...,D.
Easton et al.  

Staggered Inpatient Medication Schedules

\( M \)  
The number of unique subsets of the D care units, or \( M = \sum_{j=1}^{D} (\binom{D}{j}) \).

\( C_i \)  
a binary vector \((c_{i,1}, c_{i,2}, \ldots, c_{i,D})\) representing the \( i^{th} \) subset of care units, where \( c_{i,d} = 1 \) if unit \( d \) is an element of subset \( C_i \), 0 otherwise; defined for \( i = 1,\ldots,M \).

\( S \)  
The desired minimum probability that all medications scheduled to administered at time \( t \) can be completed on time.

\( R_{ik} \)  
RHS for the chance constraints in stage 1 of the model, representing the smallest total census in the care units contained in subset \( C_i \), such that their convolved CDF \( P(R_{ik}) \geq S \).

\( I_L, I_H \)  
The minimum \((I_L)\) and maximum \((I_H)\) allowable interval between scheduled doses

\( E_k \)  
The earliest time for the \( k^{th} \) scheduled dose of the day (determined by patient waking hours), defined for \( k=1,\ldots,3 \).

\( L_k \)  
The latest time for the \( k^{th} \) scheduled dose of the day, defined for \( k=1,\ldots,3 \), where \( I_l \leq L_k - E_k \leq I_H \).

\( T \)  
The number of consecutive 30 minute intervals in the planning horizon, indexed \( t=1,\ldots,T \).

\( W_t \)  
The number of clinicians assumed to be on duty during planning interval \( t \), defined for \( t=1,\ldots,T \).

**Decision and consequence variables**

\( X_{i,k,t} \)  
1 if the \( k^{th} \) scheduled medication time for care units in subset \( C_i \) is interval \( t \), 0 otherwise; defined for \( i=1,\ldots,M; k = 1,\ldots,3 \), and \( t=E_k,\ldots,L_k \).

\( t_{d,k} \)  
cardinal value of \( t \) when \( X_{i,k,t} = 1 \).

\( Y_{ij} \)  
number of treatments scheduled for interval \( i \) that we plan to complete during interval \( j \), defined for \( i=1,2,\ldots, T \) and \( j = i-2, i-1,\ldots, i+2 \).

\( Z_t \)  
number of late or omitted treatments that were originally scheduled for interval \( t \).

The first stage of our two-stage stochastic program involves a “here and now” decision that must be made before the realization of any uncertain events; choosing scheduled medication times for each care unit or subset of care units. As a first cut, we modeled the stage 1 problem as a chance-constrained stochastic program using RT patient census estimates for each subset of care units at the 90\(^{th}\) \%ile, with the objective of minimizing the number of late medications.

**Stage 1 Model: Chance Constrained Staggered Medication Times**

**Objective:**  
\[ \text{Minimize} \sum_{t=1}^{T} Z_t \]  \hspace{1cm} (1)

**Subject to:**
Assign a scheduled medication time for the kth treatment of the day to each care unit.

\[ \sum_{c_{i,d}}^{d} \sum_{i=1}^{M} c_{i,d} X_{i,k,t} = 1, \text{ for } k=1,\ldots,3 \text{ and } d=1,\ldots,D \]  

(2)

Assign at most one subset of the care units to a particular scheduled medication time.

\[ \sum_{i=1}^{M} X_{i,k,t} \leq 1, \text{ for } t = 1,\ldots,T \text{ and } k=1,\ldots,3 \]  

(3)

Ensure the scheduled medication times fall within clinically effective intervals.

\[ t_{d,k} = \sum_{c_{i,k}}^{d} \sum_{i=1}^{M} c_{i,d} X_{i,k,t}, \text{ for } d=1,\ldots,D \text{ and } k=1,\ldots,3 \]  

(4)

\[ l_{L} \leq t_{d,k} - t_{d,k-1} \leq l_{H}, \text{ for } k = 2 \text{ and } 3. \]  

(5)

Schedule medication times during patient waking hours; observe other time-of-day constraints on scheduled medication times.

\[ t_{d,k} > E_{k}, \text{ for } d=1,\ldots,D \text{ and } k=1,\ldots,3 \]  

(6)

\[ t_{d,k} < L_{k}, \text{ for } d=1,\ldots,D \text{ and } k=1,\ldots,3. \]  

(7)

Avoid interfering with other higher-priority scheduled routines

\[ X_{it} = 0 \text{ for } t = \text{ normal times for shift changes and physician rounds} \]  

(8)

**Recourse Decisions:**

Allocate available clinicians to scheduled medications within the allowed time window (+/- 1 hour or +/- 2 planning intervals of the scheduled medication time).

\[ \sum_{i=1}^{M} R_{i} X_{i,k,t} \leq W_{t}, \text{ for } t=1,\ldots,T \]  

(9)

Compute scheduled workload for each period

\[ R_{t} = \sum_{i=1}^{M} R_{i} X_{i,k,t}, \text{ for } t = 1,\ldots,t \]  

(10)

Compute number of late/omitted treatments conditioned on planned workload \( R_{t} \)

\[ R_{t} - \sum_{i=t-2}^{t+2} Y_{t,i} - Z_{t} \leq C_{t}, \text{ for } t=1,\ldots,T \]  

(11)

Non-negativity and integrality constraints.

\[ X_{i,k,t} \in \{0,1\}, Y_{i,t} \text{ and } Z_{t} \geq 0 \text{ } \forall \text{ k and t.} \]  

(12)

The object of a chance-constrained model is to find solutions for which the chance of an undesirable outcome (a tardy medication) is small. In this model, a solution with an optimal value (OV) of zero indicates that the budgeted staffing levels \( W_{t} \) are sufficient to achieve the
prescribed probability of completing all scheduled medications on time. If the OV for equation (1) is greater than zero, then the targeted service levels for one or more planning intervals cannot be achieved with the budgeted resources. The options are to either increase RCP capacity, perhaps through holdover overtime (Easton & Goodale, 2005), or to relax the targeted service levels. Since the scheduled medication times will be difficult to alter once they are established, it is also important that they be reasonably robust and acceptable to all parties. With simple parameter changes or the addition of a few strategic constraints, the model can be adapted to investigate alternate scenarios. For example, our initial results produced scheduled medication times that created inefficient “tours” through the hospital for RCPs. With the addition of a few constraints, we were able to establish the impact that more efficient routes would have on on-time performance. Finally, the staff allocation variables $Y_{t,j}$ appearing in constraints (9) and (11) are recourse variables that determine how RCPs should be best deployed through time to respond to realized RT patient census.

**RCP Allocation and Assignment**

In practice, many hospitals plan the allocation of RCP clinicians to patients at the beginning of each shift, once actual staffing levels and the RT patient census are revealed. For the second stage of our two stage stochastic program, we simulate patient census by care unit or sets of care units with the same scheduled medication times, solve the RCP allocation problem to minimize late treatments, and aggregate the results into a distribution of late treatments for the chosen medication times.

By the time RCPs actually report for duty at the start of their shift, the number of RT patients on each unit is known with certainty, so specific job assignments can be planned. As before, the goal of RCP-patient assignment decisions is to maximize the number of scheduled medications that are administered on time. At this phase of the process, however, clinicians need to know the patient identity, location, and time of the scheduled treatments they are expected to perform. Management also needs to know whether additional capacity will be needed so they can mobilize additional resources such as overtime labor to avoid any anticipated late treatments. Finally, to implement the primary care treatment model, we may wish to pair RCPs with inpatients whom they have treated previously and have established some rapport.

In addition to the notation defined for the stage 1 model, let: $r_{d,t}$ be the actual number of RT patients in care unit $d$ with scheduled medications due during interval $t$; $Y_{t,d,j}$ = number of RCPs allocated to department $d$ during period $j$ to administer medications that were scheduled for period $t$; and $Z_{d,t}$, the number of treatments in care unit $d$ that were due during interval $t$ but cannot be completed within the allowed time.

**Stage 2 Model: RCP Allocation Decisions**

\[
\text{Minimize } \sum_{t=1}^{T} \sum_{d=1}^{D} Z_{t,d} \tag{13}
\]

Subject to:

Assign available RCPs to administer scheduled treatments within the allowed time window and record number of late treatments.

\[
\sum_{d=1}^{T-2} Y_{t,d,\sigma} + Z_{t,d} = r_{d,t}, \text{ for } d=1,\ldots,D \text{ and } t=1,\ldots,T \tag{14}
\]
Allocate at most $W_t$ therapists during period $t$, or

$$\sum_{d=t-2}^{t+2} Y_{t,d,s} \leq W_t, \text{ for } t=1,\ldots,T$$

(15)

$$Y_{t,d,s} \geq 0, \text{ for } t=1,\ldots,T; d=1,\ldots,D; \text{ and } t-2 \leq s \leq t+2.$$  

(16)

The expectation of the outcome from these decisions can be obtained by sampling from the distribution of RT patient census values (i.e., $r_{ds}$) and solving the allocation problem repeatedly. However, in its current form, this approach suffers from two limitations. First, the performance expectations from stage 2 do not influence the stage one decisions. Based on preliminary results (see section 4) however, the dramatic improvement obtained with this approach suggests that in some cases, this limitation is not particularly serious. Another limitation that could have far more important consequences is that model identifies late medications but provides no guidance about the best ways to rectify the shortfall. Because an unaddressed late treatment eventually becomes a missed treatment, it can lead to more serious consequences for patients. Thus, some administrative mechanism is needed to mobilize resources available through holdover overtime or float staff to address anticipated late medications.

### Dispatching Model

One additional limitation of the allocation model presented in the previous subsection is that it addresses only one of the stochastic elements affecting on-time medication performance. Hospitals are by their nature complex, dynamic systems with processes that must be adapted to the needs of each patient; a perfect setting to induce variability in the times that inhaled medications are administered. For example, at their scheduled medication times some RT patients may be conversing with their doctor on “rounds” or eating a meal, or be out of their room undergoing tests at another location; all common reasons given for late administration of prescribed drugs. Alternatively, the RCP who is scheduled to administer the patient’s medication may be responding to an emergency or treating a newly admitted patient who was not included in the original allocation plan, and is unable to administer a scheduled medication for a patient at the time originally planned. These and other unplanned events suggest that the planned treatment schedule laid out in the initial allocation plan prepared at the beginning of a shift is almost certain to become obsolete shortly after it is printed.

Of course, hospitals aren’t the only systems that must contend with such uncertainties. In manufacturing environments, planners often rely on metrics such as critical ratios to help flag jobs in danger of becoming tardy. For example, Chiang and Fu (2004) adapted the “Critical Ratio” to prioritize work in flexible manufacturing systems, where their goal was to maximize on-time completions. Critical ratios can also help direct RCPs’ attention to patients whose scheduled medications are approaching lateness and, when appropriate, redirect clinical resources to avoid late medications. Since it takes about 30 minutes to administer inhaled medication and CMS considers a medication to be on-time as long as it is administered within 60 minutes of the scheduled time, let $L_{jk}$ be the latest start time for the $k$th scheduled medication for patient $j$, $t$ be the current time, and $P$ be the expected time needed to administer the medication. Define the critical ratio for patient $j$ as $CR_j = (t - L_{jk})/P$, where in general, smaller CRs indicates higher priorities. For the administration of inhaled medications, patients with CRs less than 1 are already late and should be accorded the highest priority, while patients with CRs greater than 4 are not yet within the allowed time window (e.g. +/- 60 minutes of scheduled
administration time) for their next medication. To be effective, CR priorities require current information about the status of all scheduled medications. Thus we recommend that they be implemented as part of the computerized provider order entry systems used by many hospitals.

**COMPUTATIONAL STUDY, RESULTS, AND DISCUSSION**

To evaluate the feasibility of our methodology, we worked with a 350 bed acute-care hospital that treats patients with breathing disorders in 24 different care units. Over a six month study period, about 25% of their RT patients were treated in six departments that for clinical reasons, had permanently-assigned RCPs on the floor. On average, 37.0 RT patients/day were being treated in one of six other care units in the hospital, and the rest (0.76 RT patients on average) were dispersed over the remaining twelve care units in the hospital (hereafter referred to as the “other” care units.) However, most (> 60%) RCPs administer medications in just one or two care units. Our strategy calls for routing RCPs as a team from care unit to care unit throughout the hospital, supporting a primary care treatment model while simultaneously pooling random demand for service.

A query of the pharmacy information system showed that 20,734 doses of respiratory drugs were administered in those 18 care units during the six-month study period. Most (98.8%) were administered with nebulizers three times per day (TID). Table 2 shows the average number of RT drugs administered in each care unit during the morning, afternoon, and evening medication times. Although we were unable to measure the variation about these means, RT department heads acknowledged that the number of treatments varied from day to day and agreed that the number of patients receiving inhaled medications in each care unit rarely exceeded the values in the three rightmost columns of Table 2. Those values correspond to the 90%ile of Poisson-distributed random variables with equal to the E(RT patients) side of Table 2.

Hospital administrators and clinicians both noted that with its large average RT patient census, it was often difficult to complete all scheduled medications in care unit 6NIR. They suggested that the RT patients in 6NIR be divided into two smaller, more manageable “virtual” care units that could have different scheduled medication times. With RT patient census at the 90th %ile in all care units, RCPs would have to administer 179 inhaled medications every 24 hours. Based on an average of 30 minutes per nebulized medication, hospital administrators suggested the following RCP staffing levels: five RCPs working days (07:00 – 15:00), four working eves (15:00 – 23:00), and two working nights (23:00 – 07:00).
To establish a baseline for comparison with the staggered medication schedules, we first evaluated on-time medication performance under a common medication time schedule. For this part of the study we set 09:00, 13:00, and 17:00 as the common medication times for TID drugs, the times used by hospitals such as the University of Washington Hospital system for their TID medications. Figure 1 shows the distribution of late treatments for 100 replications of simulated RT patient census, assuming the actual RT census follows a Poisson distribution with expectations for the number of patients receiving the the $k^{th}$ medication of the day shown in the leftmost four columns of Table 2 and RCPs are allocated using the Stage 2 model from the previous section to minimize late medications. The number of late medications under the common medication schedule averaged 43.6 with a standard deviation of 10.9.

We then repeated the study with the staggered scheduled medication times $T(d,k)$ shown in Table 3, which were recommended by the stage one medication time model described in the previous section. However, we first divided care unit 6NIR, which has the largest expected RT patient census, into two separate wings and allowed up to two different care units to share the same scheduled medication time. In all, this resulted in $M = 36$ different combinations of care units that would be eligible for a particular medication time. For each subset $C_i$, we used the CDF for the convolved distribution of total patient census for the care units in $C_i$ to determine the 90th %ile patient census ($R_{ik}$) for the $k^{th}$ medication of the day. At the assumed census levels, the chance constrained model was unable to find a way to complete 5 of the 179 scheduled treatments on time, establishing that the proposed RCP staffing levels are not, by themselves, sufficient to handle all scheduled RT medications at high levels of demand. Another noteworthy feature of the solution to the medication timing model is that it recommends that some care units share common medication times. For example, patients in care units 4NIR and 6SIR are scheduled to receive their first medication of the day at 10:00. The solution may groups units together when the 90th %ile census for their convolved census distribution is less than the sum of the 90th %ile census for each individual care unit; an important advantage when RCPs are very busy.

Finally, we simulated RT patient census for each care unit and computed the number of late medications by solving the RCP allocation model. The histogram in Figure 2 shows the
Table 3: Recommended Staggered RT Medication Schedules $T(d,k)$ for each Care Unit.

<table>
<thead>
<tr>
<th>Unit d</th>
<th>$T(d,1)$</th>
<th>Unit d</th>
<th>$T(d,2)$</th>
<th>Unit d</th>
<th>$T(d,3)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>5SIR</td>
<td>5:30</td>
<td>5SIR</td>
<td>12:30</td>
<td>5SIR</td>
<td>19:30</td>
</tr>
<tr>
<td>Other</td>
<td>6:30</td>
<td>6NIR_W</td>
<td>13:30</td>
<td>6NIR_W</td>
<td>19:30</td>
</tr>
<tr>
<td>6NIR_W</td>
<td>8:00</td>
<td>4SIR</td>
<td>13:30</td>
<td>4SIR</td>
<td>21:00</td>
</tr>
<tr>
<td>4SIR</td>
<td>8:00</td>
<td>Other</td>
<td>14:00</td>
<td>4NIR</td>
<td>21:00</td>
</tr>
<tr>
<td>4NIR</td>
<td>10:00</td>
<td>4NIR</td>
<td>15:30</td>
<td>Other</td>
<td>21:30</td>
</tr>
<tr>
<td>6SIR</td>
<td>10:00</td>
<td>6SIR</td>
<td>15:30</td>
<td>6SIR</td>
<td>21:30</td>
</tr>
<tr>
<td>6NIR_E</td>
<td>11:00</td>
<td>6NIR_E</td>
<td>17:30</td>
<td>6NIR_E</td>
<td>0:30</td>
</tr>
<tr>
<td>7MEM</td>
<td>11:00</td>
<td>7MEM</td>
<td>17:30</td>
<td>7MEM</td>
<td>0:30</td>
</tr>
</tbody>
</table>

Distribution of the number of late medications. Overall, under the recommended staggered medication times the number of late medications averaged 1.72 per day. In nearly half the cases, all scheduled medications were completed on time but in 7% of the cases there were between 6 and 8 late medications. Fortunately, we found that all but one of these tardy medications could be completed on time by extending the shifts of one or two RCPs for at most one hour (ie, using “holdover” overtime) beyond the normal shift change times.

Figure 2: Distribution of late medications with staggered medication times.

CONCLUSIONS

In this study, we examine a large, important health care quality problem that arose as an unintended consequence of efforts to improve on-time medication administration. We proposed a set of four interrelated models to (1) establish staggered medication times for RT patients; (2) determine work schedules for each RCP to ensure a high probability of meeting the resulting due dates; (3) allocate RCPs to patients at the beginning of each shift; and (4) monitor schedule program and adjust in real time as unexpected variation in the schedule appears. This report focuses on two of those models. For each, the goal is the same: minimize the number of late medications. After describing the proposed methods, we apply the techniques to scenarios
based on actual data supplied by a 350 bed hospital in our region. The results suggest that the proposed methodology is efficient and capable of dramatically reducing late treatments.

The study does not capture all of the variability that RCPs face each day, so it is our intention to extend this study by simulating the effects of patient and clinicians availability on schedule performance. Although we also intend to develop a deterministic equivalent of the 2-stage stochastic program, the 96% reduction in late treatments achieved by the present approach leaves few opportunities for further improvement.

REFERENCES:


