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PHYSICIAN SHIFT BEHAVIOR AND ITS IMPACT ON SERVICE PERFORMANCES IN AN EMERGENCY DEPARTMENT

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ABSTRACT

Simulating detailed flow through emergency departments (ED) has been a long-standing issue. By studying the behavior of the bottleneck resource, the physicians, we have identified key factors to include in a simulation that have allowed us to create an extremely accurate model of a specific ED. The impact of these factors was evaluated through several performance measures in the ED. We conclude that it is important to consider the inclusion of physician behaviors when simulating ED wait times.

1 INTRODUCTION

In Canada, reducing wait time is one of the major objectives of healthcare providers. In 2004, the province of Ontario launched the "Wait Time Strategy" to improve access to services (MOHLTC 2004). In 2007, the strategy was expanded to address ED wait times in hospitals (MOHLTC 2007). In fact, ED wait times in Canada have attracted considerable public and research attention (Schull 2005; Rowe et al. 2006; CIHI 2007; Guttmann et al. 2011; CIHI 2012).

Simulations of hospital EDs have been created for decades to understand and improve the patient flows related to wait times (Draeger 1992; McGuire 1997; Jun et al. 1999; Hoot and Aronsky 2008; Holm and Dahl 2009; Eskandari et al. 2011; Cabrera et al. 2012). When building a simulation model, one of the critical questions is: What level of detail should be included (Teorey and Merten 1973)? The answer is that it depends on the objectives of the simulation model. As Jurishica (2005) discussed, a tradeoff exists between the value of an ED simulation project and the level of detail in general, with the correct level of detail being determined by the project's objective. Komashie and Mousavi (2005) also pointed out that in most cases, 80% of model accuracy is obtained from only 20% of the model's detail.

When addressing the ED problem, if the simulation is to answer overall usage or performance at the day or week level, it is possible to ignore within-day validity. For example, if the overall capacity is capable of satisfying the overall demand every twenty-four hours, and the question is related to overall resource provision, then queuing behavior within the day is secondary. Unfortunately, the ED wait time question pertains to the queuing situation within the day, and this implies that some level of detailed validity is required throughout the day.

In 2011 an extensive analysis was performed of a medium-sized community hospital in Ontario, Canada, and it was identified that the bottleneck resources were the emergency physicians (McKay et al. 2013). The analysis also pointed out a number of shift-related behaviors that the majority of physicians exhibited. However, a review of the literature showed that historically the physician resource has been modeled at a high level without any detailed data regarding behavior during the shift. For example, in a number of papers, such as Samaha et al. (2003), Ahmed and Alkhamis (2009) and Kuo et al. (2012), the physician resource is modeled using a fixed shift length with either constant or uniform productivity throughout the shift. Since we had observed otherwise in 2011, it was decided that the potential value of incorporating the physician behaviors should be explored. This exploration served as part of validation process for our simulation model that was addressing the wait times in the ED.

A four-phase model of physician behavior during a shift, as well as several other behavioral factors is introduced in the next section, then the simulation and experimentation on the factors are presented. This paper concludes with a discussion on the importance of including physicians' behaviors for an ED simulation addressing the wait time problem.

2 PYSICIAN BEHAVIORS

ED physicians, as the bottleneck of many ED systems, have a great impact on wait times. Based on our field study in an ED, we found ED physicians' behavior to be structurally different during a shift. We believe this structural difference helps explain part of the service variance and ED wait time performance. Based on our field study, a four-phase model describing the structure of ED physicians' behavior during a shift was constructed. The model divides a typical physician shift into a *start-of-shift* phase(the first hour of the shift), a *mid-shift* phase (the next five hours) , a *cleanup* phase (the next 1.5 hours), and a *transfer out* phase (the last half hour). Figure 1 shows how the four-phase model applies to a shift. In the *start-of-shift* phase, the physicians started their work with the patients inherited from the previous shift (inherited charts) and/or new critical patients (new charts) depending on the situation in ED. There are two queues for the physicians: i) inherited charts, the patients who arrived during a previous shift; and ii) new charts, the charts as prepared by the registered nurses as patients arrive during the shift. In the *mid-shift* phase, as previous work gets cleaned up and new critical ones have been handled, new normal work (non-critical charts) is started. In the *cleanup* phase, as the shift approaches its end, the physicians mainly conduct second assessments and disposition for their patients or typically pick 'quick' charts to deal with, such as patients that could be seen and fully processed before the end of shift. The very last phase of a shift, the *transfer-out* phase, was usually consumed by transfer discussions with the incoming physician and other relevant staff. Additionally, throughout the shift, the physicians were involved in other activities, we have referred to as "Helping Others" in Figure 1, such as teaching residents, consulting with other clinicians, or having a meal break.

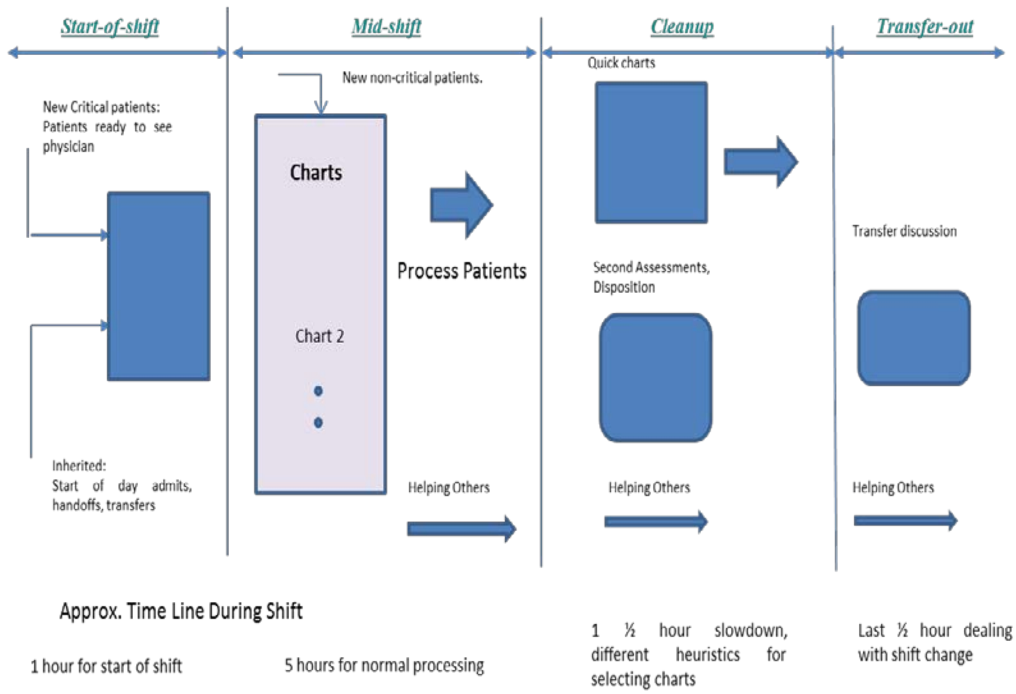

Figure 1: Physician four-phase model during a shift.

We found that physicians processed cases differently at each phase of a typical shift. This particular four-phase model may be specific to this hospital, and others might have more or fewer phases. The key concept is that there may be different within-shift behavior of the bottleneck resource to capture and model within the department.

The first implication from the four-phase model is that the speed of physician initial assessment (PIA) for patients varies considerably at different phases. The second implication is that because activities other than seeing patients in the ED are more intense during the day shift, the model implies that the speed of physician assessment in the day shift is slower than that in other shifts.

To verify the two implications suggested by our four-phase model, as can be seen in Figure 2, we plotted the average PIA rate—the number of new patients seen by physicians per hour—across the day based on historical data. In the ED studied (detailed information about this ED can be found in McKay et al. (2013)), there were five eight-hour overlapping shifts with start times of 0730 hours, 1000 hours, 1600 hours, 1700 hours and 2400 hours. In Figure 2 the start of shifts is indicated by square, the end of shifts is indicated by triangles, and meal is indicated by circles.

To examine the first implication identified from our four-phase model, we matched the shift start (indicated by solid arrows in Figure 2) and shift end (indicated by dash arrows) in the PIA rate graph. The last two hours of each shift are regarded as the "shift end", since physicians slow down and wrap up their work during this period. Therefore, in the graph, the shift end triangles do not point to exact end shift points in time, but roughly indicate this last period. From the graph, we can see that the number of patients seen at the end of each shift (indicated by triangles) are less than the number of patients seen at the beginning of each shift (indicated by squares). This indicates a clear pattern that physicians assess less patients at the end of their shifts in support of our first implication.

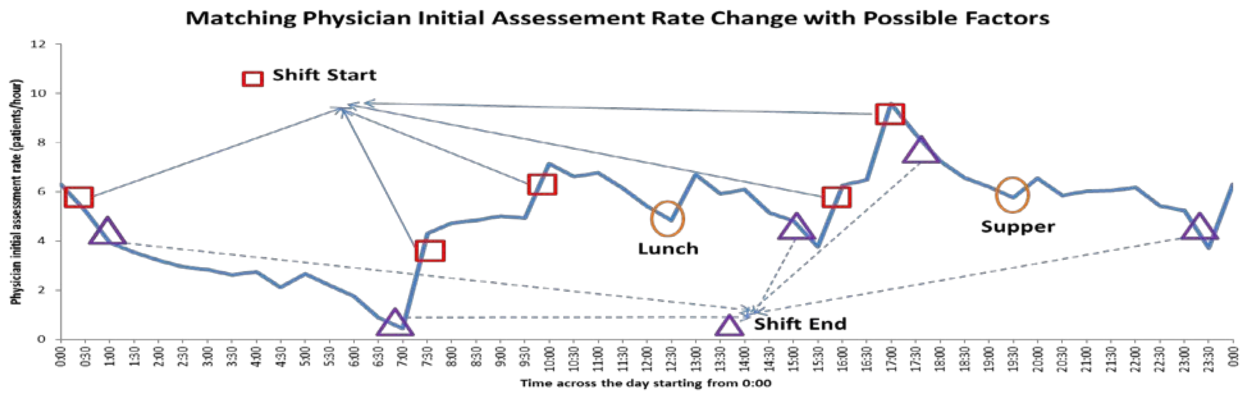

Figure 2: Physician Initial Assessment rate change across the day.

To examine the second implication from our model, we compared the PIA rate during the day shift (starting at 0730 hours and 1000 hours) with the night shift (starting at 1600 hours and 1700 hours) and the midnight shift (starting at 2400 hours). We calculated the average PIA rate per hour per physician during the different shifts. For the day shift, the average is 2.80, while for the night and midnight shifts, the average are 3.17 and 2.98 respectively. This result supported our second implication. As can be seen in Figure 2, the day shift has two deep dips (from 1100 hours to 1300 hours, and from 1400 hours to 1600 hours), while the night shifts (starting at 1600 hours and 1700 hours) and mid night shift (starting at 2400 hours) just have one deep dip each. We believe that this one more dip during the day shift contributes to the lower average PIA rate. We do not know precisely what causes the dipping behavior and that is a topic for future research.

Besides the shift start and end effects, we also find that the meal time (lunch and supper times in the graph, indicated by circles) also plays a role in forming the bumpy nature of the PIA rate change. If these physician behaviors had no effect, we would expect a relatively smooth line of average PIA change across the day except the early morning period (from 0500 hours and 0700 hours). Since the ED is almost always busy, and the physicians are the bottleneck of ED, there are very few chances for physicians to not have patients waiting, and therefore we would just see some sudden change of PIA rate at the point of capacity change (i.e. when there was an overlap of shifts and multiple shifts were assessing patients at the same time), but not bumps at other points. Only the 0500 hours to 0700 hours period is an exception because our data suggests that the physician at that time has almost assessed all patients waiting in the queue, and there are few new arrivals during that time.

Combining the information obtained from the physician 4-phase model with the PIA rate change pattern, we extracted 3 factors to represent physician behaviors for the purpose of evaluating the influence of physician behaviors on the ED wait time simulation problem. The first factor, "phase factor", refers to the PIA rate change within a shift. The second factor, "shift factor", refers to the PIA rate change between shifts. Finally, the third factor, "meal factor", represents the PIA rate change at meal time. In the rest of this paper we will discuss our study which examined how these three factors impact the ED wait time behavior.

3 STUDY DESIGN

The research question for this paper is: Are physician behaviors (the three defined physician behavior factors – phase, shift and meal) important to be included in simulations that study patient wait time in the ED?

To answer this question we built simulation models with and without these factors, and then we compared the results to key performance measures in the historical data. We proposed that if the models that incorporate these physician behavior factors are more similar to the historical data than the models that do not include these factors, then we could conclude that these factors should be considered when building an ED simulation model. To systematically screen these factors we used factorial experiment design. In this section we introduce our factorial experiment design, the key performance measures, and the simulation model.

3.1 Factorial Experiment Design

Since the number of factors to be examined was small, a full factorial design was conducted. We designed a 2^3 factorial experiment to evaluate the effects of the three physician behavior factors – phase, shift and meal. As shown in Table 1, the experiment has a total of eight scenarios, with each row in the table corresponding to a scenario. The numbers in each cell indicate the combination of each factor, with "1" indicating that the factor is taken into account in that scenario, and "0" indicating that it is not.

Table 1: Scenarios of 2^3 factorial experiment.

Scenario	phase	Shift	meal
Scenario 1	1	1	1
Scenario 2	1	1	0
Scenario 3	1	0	1
Scenario 4	1	0	0
Scenario 5	0	1	1
Scenario 6	0	1	0
Scenario 7	0	0	1
Scenario 8	0	0	0

3.2 Key Performance Measures

Four performance measures - PIA rate, PIA wait time, PIA queue length and patient length of stay (LOS) - were chosen as our criteria. First, we have defined PIA rate in Section 2 as the number of new patients seen by physicians per hour. It directly measures ED physicians' speed; therefore, the effect of physicians' behavior can be relatively well reflected by this measure. Second, PIA wait time is defined as the wait time that patients wait to be seen by physicians after they are triaged. Third, PIA queue length is the number of patients that are waiting for their initial assessment after triage. Like PIA rate, PIA wait time and queue length provide information on the physician initial assessment process, but from different perspectives. Finally, patient LOS is defined as the wait time from the time patients are triaged to the time patients leave the ED. It is chosen because it is an important performance measure monitored by both hospital management and the public.

3.3 Simulation Model

3.3.1 ED Patient Flow Background

In the ED studied, patients enter either by walking in or by ambulance. Because the hospital is the Region's cardiac and respiratory center, this ED sees a high number of acute patients with symptoms in these two areas. Therefore, patients arrive by ambulance will not be seen any sooner than those already waiting for care. When a patient arrives, a triage nurse assesses the acuity of his/her condition according to pre-established standards (known as the Canadian Triage and Acuity Scale -CTAS), and assigns him/her to a treatment area, either acute, sub-acute, or minor, in the ED. Then, the patient is registered by a clerk. This process usually takes around 5 to 10 minutes. The patient will then wait for a bed in the ED treatment area. Upon entering the ED treatment area, a registered nurse will prepare the chart of the patient. The patient will then wait to be seen by a physician or a Nurse Practitioner, based on their triage assessment and relative acuity compared with other patients. The physicians are capable of seeing patients from all the three treatment areas, but nurse practitioners are designated to minor patients. Physicians or nurse practitioners will usually order diagnostic tests for patients, such as X-Ray, Ultra-sound, CT scan or combinations, based on their condition. Patients may also be directed to specialists by physicians if needed. The resources for diagnostic tests and specialist consultations are shared by the whole hospital. Patients may go through physician assessment several times before they can be fully diagnosed and treated. Finally, Patients will be either admitted to the hospital or discharged. After discharge, the ED can release the bed for other patients. During the whole process, some patients (around 5%) may leave before they are seen by a physician or a nurse practitioner.

3.3.2 Conceptual Model and Model Construction

The conceptual model of our simulation is shown in Figure 3. In the model, patients arrive through non-stationary Poisson processes depending on patient type (triage level). We assume patients will not leave without treatment if they are already in the ED treatment area. They only leave without treatment in the waiting area outside. Patients are assigned to different treatment areas based on the distribution obtained from historical data. Patients from different treatment areas share the same group of physicians. Three attributes are used to determine the path of a patient in the model: (i) treatment area assigned to the patient; (ii) the number of physician assessments, and; (iii) whether the patient will be admitted to the hospital. The first two attributes are used to model the priority that physicians assign to patients. As suggested by the names of the areas, namely acute, sub-acute and minor, area is an attribute that determines the acuity of patient illness. In the system, patients who have been seen by physicians have a lower priority for reassessment by physicians than those who are waiting for an initial assessment. We use the number of assessments as an aggregated figure indicating how many tests and consults the patients have to go through. In the model we do not distinguish each specific test, because tests are performed outside of the ED, thus they are subject to the same uncertainty imposed by the whole hospital. The test times are aggregated to reassessment wait times which are fitted by exponential distribution in our model.

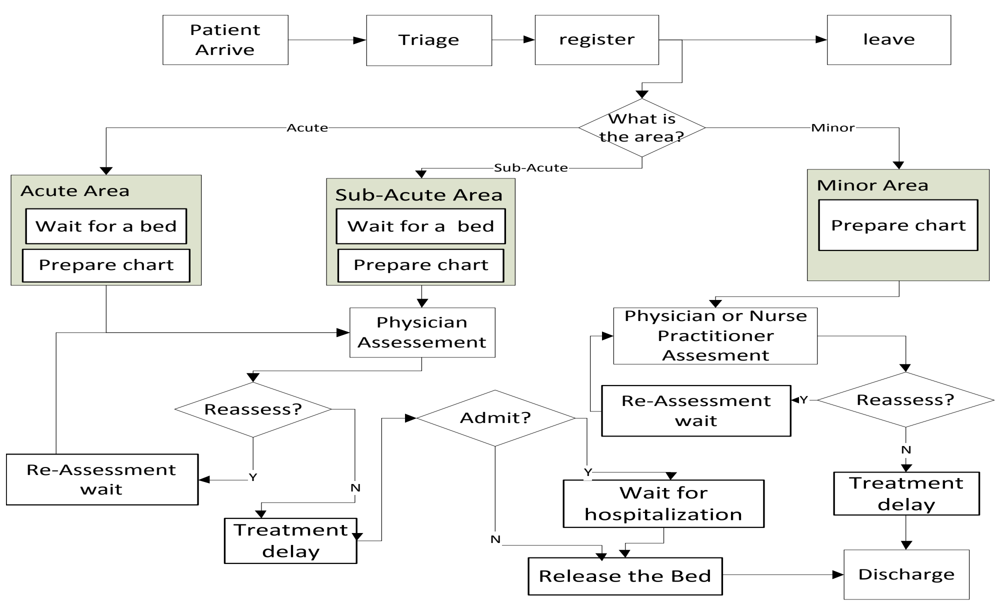

Figure 3: ED simulation conceptual model.

Arena 14 was used to construct the actual simulation model. The face validity of our model was secured by discussions with ED managers and the extensive field study (McKay et al. 2013). We used historical data to estimate the probability distributions in our model and the data was extracted from the patient record information system. The model is based on the data of April 2011 and represents approximately 4000 visits to the ED. The input data analysis was conducted in EasyFit.

We constructed eight simulation models corresponding to the eight scenarios. We then made ten replications for each model. The number of replications were calculated from the data obtained from our pilot run for Scenario 1. In the pilot run, ten replications ($\mathrm{R}_0 = 10$) were executed and data for LOS, PIA wait time, and PIA queue length were collected. The averages and standard deviations, which we paired together, from the pilot run for the three key performance measures were (5.59, 0.29), (13.32, 0.33), and (2.23, 0.06), respectively. We next computed how many replications we needed to obtain 95% confidence that the average was within a 10% range of the pilot run average based on formula (1) as following Banks et al. (2010) for each of the three key performance measures:

$$\mathrm{R} \geq \left(\frac{Z_{\alpha/2}S}{h}\right)^2. \tag{1}$$

In formula (1), R is the replication number required; $Z_{\alpha/2}$ is the 100(1-$\alpha/2$) percentage point of standard normal distribution; S is the standard deviation; and h is the half-length of a 100(1- α)% confidence interval for an average A. Based on the data above, the half-length of the confidence interval for each of the three performance measures is $5.59 * 10\% * 1/2 \approx 0.28$, $13.32 * 10\% * 1/2 \approx 0.67$, and $2.23 * 10\% * 1/2 \approx 0.11$, respectively. Using formula (1), the required replications for the three key performance measures are $R_1 \geq 3.84$, $R_2 \geq 0.97$ and $R_3 \geq 1.13$, respectively. Therefore, the final replications number is set to be $\max\{R_0, R_1, R_2, R_3\} = 10$.

4 RESULT-MODEL COMPARISON

In this section, we compare the results of the key performance measures - PIA rate, PIA wait time, PIA queue length and patient length of stay (LOS) - of each simulation model.

4.1 Model Comparison: PIA Rate

Because the number of physicians and the number of patients arriving in the ED vary across the day, we decided to examine the PIA rate pattern as a whole. Figure 4 shows the eight scenarios' PIA rate patterns across the day compared with the historical data. The simulation result is indicated by the solid lines and the real historical PIA rate is indicated by the dash lines. As can be seen in the figure, Scenario 1 considers all the factors and has the closest similarity with the historical data; whereas Scenario 8 does not take any factors into account, and the ups and downs disappear in the simulated PIA rate. Comparing Scenario 1 (all factors) with Scenario 4 (only phase factor), we can see that phase factor determines the general pattern of the PIA rate change across the day. Furthermore, comparing Scenario 1 with Scenario 3 (no shift factor) and Scenario 6 (only shift factor) , we see that the shift factor is important to close the gap between the simulation result and the historical result, especially for the day time period. Finally, comparing Scenario1 with Scenario 2 (no meal factor) and Scenario 7 (only meal factor), we can conclude that the meal factor is a critical factor to form the dips at meal times.

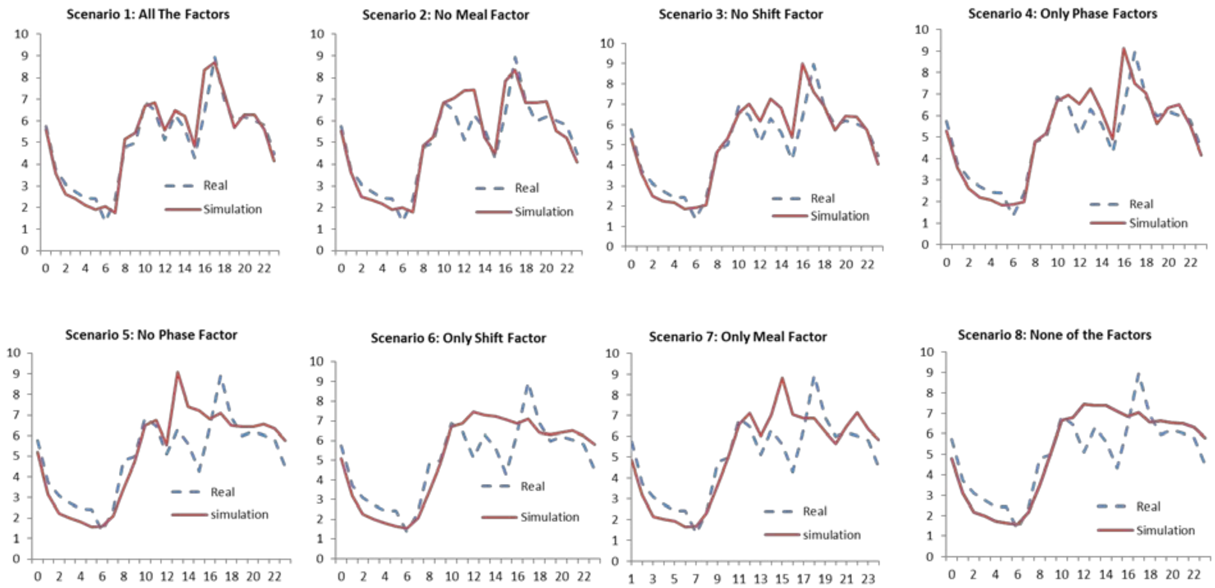

Figure 4: PIA rate change pattern of the eight scenarios compared with historical pattern.

4.2 Model Comparison: LOS, PIA Queue Length and PIA Wait Time

For each of the eight simulation models, we collected the average of LOS, PIA queue length, and PIA wait time in each of its ten replications. For each of the three measures, we then calculated the average and the 95% confidence interval based on the 10 replications' data for each scenario. We compared these averages with the historical average, and the result is shown in Figure 5. Only Scenario 1's confidence interval covers the historical result.

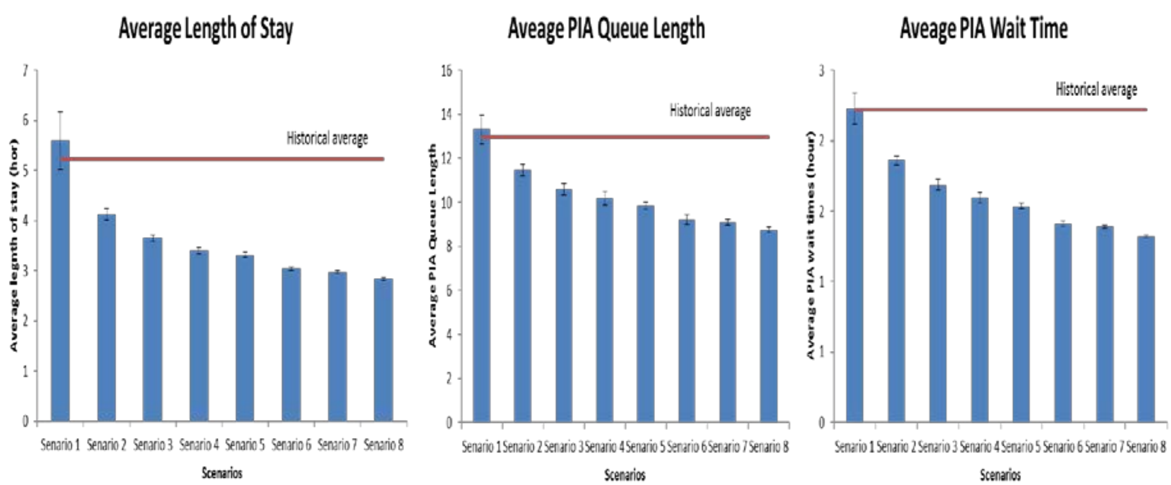

Figure 5: Average LOS, PIA queue length, and PIA wait time of the eight scenarios compared with the historical average.

We also calculated the absolute percentage by which each scenario's average deviated from the historical average. The results are shown in Table 2. Only the results from Scenario 1 are reasonably close to the historical averages, as the errors in this scenario are less than 10%. In contrast, the errors in Scenario 8 are as high as 45.7% for LOS, 32.6% for PIA queue length, and 40.5% for PIA wait time. The errors in all other scenarios reside within the range between these two extreme cases, and are also unacceptable.

Table 2: Errors of the 8 scenarios compared with historical data.

	LOS(hours)			PIA queue length			PIA wait time (hours)		
Scenarios	Average	Std Dev	|Error|	Average	Std Dev	|Error|	Average	Std Dev	|Error|
Historical	5.23	---	---	12.98	---	---	2.22	---	---
Scenario 1	5.59	0.29	6.9%	13.32	0.33	2.6%	2.23	0.06	0.5%
Scenario 2	4.13	0.06	21.0%	11.49	0.13	11.5%	1.86	0.01	16.2%
Scenario 3	3.66	0.03	30.0%	10.59	0.13	18.4%	1.69	0.02	23.9%
Scenario 4	3.40	0.03	35.0%	10.19	0.15	21.5%	1.59	0.02	28.4%
Scenario 5	3.32	0.03	36.5%	9.85	0.15	24.1%	1.53	0.01	31.1%
Scenario 6	3.04	0.02	41.9%	9.23	0.11	28.9%	1.41	0.01	36.5%
Scenario 7	2.98	0.02	43.0%	9.10	0.08	29.9%	1.38	0.01	37.8%
Scenario 8	2.84	0.01	45.7%	8.75	0.06	32.6%	1.32	0.01	40.5%

We further conducted the ANOVA analysis on the data to evaluate the effect of the three factors and their interaction on LOS, PIA queue length and PIA wait time. The result is shown in Table 3.

Table 3: Variability contributed by different factors.

	LOS		PIA queue length		PIA wait time	
Factor	Sum of Squares	Percent of Contribution (%)	Sum of Squares	Percent of Contribution(%)	Sum of Squares	Percent of Contribution(%)
P	26.5	46.2	93.9	58.6	3.7	58.9
S	12.8	22.4	34.7	21.6	1.4	21.7
M	5.7	10.0	12.9	8.0	0.5	8.5
PS	5.6	9.8	9.7	6.1	0.4	6.4
PM	2.1	3.7	2.0	1.3	0.1	1.4
SM	2.3	4.0	3.6	2.3	0.1	2.2
PSM	1.4	2.4	1.7	1.1	0.1	0.9

*In the table, P is for Phase factor, S for Shift and M for Meal; PS is the interaction term between phase and shift, and so on so forth. The P-values of all the factors are smaller than 0.01.

In Table 3 the sum of squares is the variability that the factors account for. The percent of contribution measures the percentage contribution of each model term to the total sum of squares. It is often a rough, but effective guide to the relative importance of each model term (Montgomery 2008). As can be seen from the table, the phase factor (P) accounts for around half of the total variability for all the three key performance measures, followed by the shift factor (S) that accounts for around one fifth of the variability.

5 IMPLICATION

The results from the previous section demonstrate the importance of including physician behaviors in the simulation model when simulating the ED wait time. In this section we discuss how the physician behaviors can be exploited to improve the ED performance.

During our study, the ED decided to add an extra shift to mitigate the wait time problem. As mentioned above, the original five shifts (the base case) start from 0730 hours, 1000 hours, 1600 hours, 1700 hours and 2400 hours respectively. After considering that most of the patients arrive during the daytime, two alternatives initially considered are to add an extra 0730 hours shift or a 1000 hours shift. However, after recognizing that the physician behaviors make the speed of physician assessment vary considerably in the beginning and end of the shift, we proposed a third alternative: that the eight hour shifts should be started every four hours. In this way, the shift beginning and shift end period overlap, so that a reduction in the variation of physician assessment speed caused by physician behaviors can occur.

We executed ten replications[1] for each alternative with the simulation model that incorporated the physician behavior. We graphed the boxplot for the three key performance measures: LOS , PIA queue length and PIA wait time based on the ten replication data in Figure 6. The figure clearly shows that the "every 4 hours" alternative achieves better performance than do the other two alternatives in terms of the three performance measures.

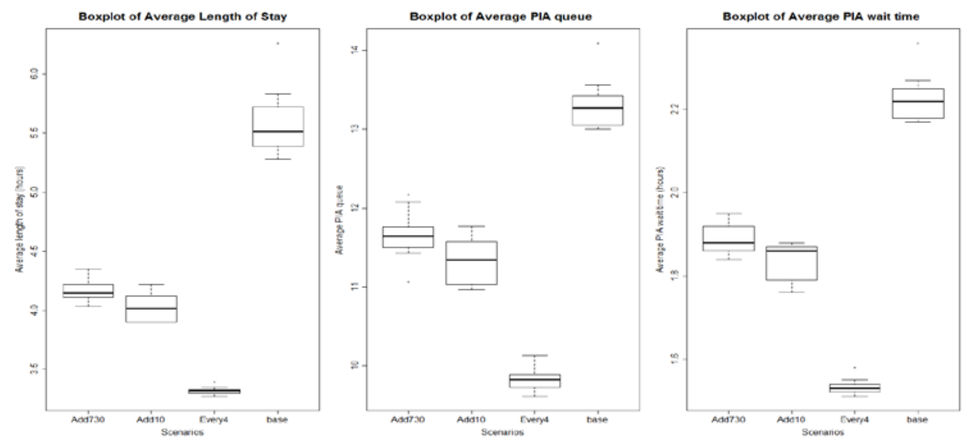

Figure 6: Comparison of LOS, PIA queue length, and PIA wait time for each alternative based on ten replication data.

We calculated the average and standard deviation of LOS, PIA queue length and PIA wait time for each alternative as shown in Table 4. The "every 4 hours" alternative achieved 41% reduction on average for LOS, 26% on PIA queue length, and 31% on PIA wait time. The results of the other two are quite close, their reduction on these measures much smaller than the every 4 hours'.

Table 4: Result of LOS, PIA queue length, and PIA wait time of each alternative.

No.	Alternatives	LOS(hours)			PIA queue length			PIA wait time (hours)		
		Avg.	Std Dev	Reduction	Avg.	Std Dev	Reduction	Avg.	Std Dev	Reduction
1	Base case	5.59	0.29		13.32	0.33		2.23	0.06	
2	Add an extra 0730 shift	4.17	0.11	25%	11.66	0.32	12%	1.89	0.04	15%
3	Add an extra 1000 shift	4.03	0.12	28%	11.34	0.3	15%	1.83	0.06	18%
4	Every 4 hours	3.32	0.03	41%	9.83	0.14	26%	1.53	0.02	31%

[1] Formula (1), discussed in Section 3.3.2 was used to determine that 10 replications was appropriate.

6 CONCLUSION

From the study, we confirmed the field study result that ED physician behaviors have a great impact on the ED wait time performances. When we build simulation models to study the ED wait time problem, we should not ignore the physician behaviors in our models. They may or may not be significant, but they must be analyzed before being discounted. ED management that intend to improve ED wait time performance should also incorporate these insights into their decision making process.

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