Using Simulation to Examine the Effect of Physician Heterogeneity on the Operational Efficiency of an Overcrowded Hospital Emergency Department

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Abstract. In this paper, we present a case study of modelling and analyzing the patient flow of a hospital emergency department in Hong Kong. The emergency department is facing the challenge of overcrowding and the patients there usually experience a long waiting time. Our project team was requested by a senior consultant of the emergency department to analyze the patient flow and provide a decision support tool to help improve their operations. We adopt a simulation approach to mimic their daily operations. With the simulation model, we conduct a computational study to examine the effect of physician heterogeneity on the emergency department performance. We found that physician heterogeneity has a great impact on the operational efficiency and thus should be considered when developing simulation models. Our computational results show that, with the same average of service rates among the physicians, variation in the rates can improve overcrowding situation. This suggests that emergency departments may consider having some efficient physicians to speed up the overall service rate in return for more time for patients who need extra medical care.

1. Introduction

Emergency department (ED) overcrowding is a longstanding and serious issue confronting many countries and cities around the world (e.g., [1-5]), and this phenomenon is observed to be deteriorating [6, 7]. Originally, EDs are established to provide immediate medical care to critically ill or severely injured patients, who have a very high risk of morbidity and mortality if not treated speedily and properly. Thus, timeliness and efficiency are their core attributes [8]. However, due to various causes of overcrowding, e.g., increased complexity and acuity of patients presenting to EDs, overall increase in patient volume, managed care problems and lack of beds for patients admitted to hospitals [9], EDs sometimes are not capable of delivering timely medical care to patients. Failure to provide timely and adequate medical care to patients can be life-altering, and even life-ending: causing undue injuries and even unnecessary deaths of emergency patients. Besides, ED overcrowding can also result in other negative outcomes such as public safety at risk, prolonged pain and suffering, and long waits and
dissatisfaction of patients [9]. Although both academics and practitioners have been trying to improve ED efficiency for decades, many EDs are still crowded on a daily basis. A main reason for ED overcrowding being insoluble is that most solutions to the problem are in general costly, e.g., replacing and upgrading ED facilities and expanding workforce. Most non-profit hospitals have only limited financial budgets so that these options are infeasible to them. For this reason, hospital administrators need to explore other alternatives to resolve the overcrowding problem. One way to relieve the poor situation is to enhance ED operational efficiency, for example assuring that valuable resources, such as physicians and nurses, are well-utilized.

The Prince of Wales Hospital (PWH) is one of the largest public general hospitals in Hong Kong and also the teaching hospital for the Faculty of Medicine of the Chinese University of Hong Kong. It has around 1,500 hospital beds and 4,500 staff, and serves the region of New Territories East (more than 1.5 million people). The ED of PWH, which provides 24-hour Accident and Emergency (A&E) services and has an annual attendance of 157,719 [10], is also facing the challenge of overcrowding. Due to the high quality of emergency care and the very low service charge (HKD 100, around USD 12.5, per attendance), there is often inappropriate use of the ED by non-urgent patients [11]. All of these together with the very serious understaffing situation have led to the ED overcrowding problem [12]. As a result, non-critical patients may need to experience a very long waiting time of several hours. The problems of overcrowding and long patient-waiting-times not only worsen patient satisfaction, but also may be barriers to patient access to appropriate and timely medical care.

Our project team was requested by a senior consultant at the ED of PWH to analyze the patient flow and help improve their daily operations. Our project goals are:

i. Measure and analyze patient flow and throughput of the ED.

ii. Model the daily operations and identify bottlenecks in the system.

iii. Evaluate possible changes in the processes that might enhance the ED performance.

iv. Improve patient flow and also patient experience.

Some of our previous work on this project can be found in [13].

Developing an analytical model for the entire system of an ED is very challenging due to uncertainty (e.g., stochastic patient arrivals and service durations) and the very complicated system (e.g., different categories of patients, non-stationary arrival rates, and re-entrant flows to the many “service stations”). For this reason, we adopt a simulation approach to investigate the processes of the ED and, by using the model, analyze the patient flow. This allows us easily to incorporate randomness into the system and to evaluate impacts of various changes in the system on the ED performance. From a practical standpoint, a simulation model is particularly helpful to hospital administrators and practitioners, who are not necessarily equipped with advanced mathematical knowledge, as they can effortlessly understand the model logic from the simulation animations and can examine many “what-if” scenarios, with outputs of their familiar key performance indicators (KPIs), within a user-friendly graphical interface.

Our paper is organized as follows. In the next section, we give a brief literature review on using simulation to model ED systems. In section 3, we describe our ED simulation model. In section 4, we conduct a computational study of the impact of physician heterogeneity on ED performance. In section 5, we conclude our work.
2. Brief Literature Review

Simulation has been used for about half a century (e.g., [14]) and is still one of most commonly-employed tools for analyzing healthcare delivery systems. For an overview of the applications of simulation to healthcare management, we refer the reader to [15-18].

According to [19], the number of articles related to the use of simulation in the domain of healthcare management is expanding at an incredible rate of 30 articles per day. Surprisingly, only 8% of the articles actually applied simulation to a real healthcare problem where real data was used [20]. This indicates that researchers still need a substantial effort to promote real implementations of simulation in the healthcare industry.

Here we review some of those successful applications. Rossetti et al. [21] used simulation to examine different physician work schedules and evaluate their impacts on patient throughput and resource utilization in an ED in Charlottesville, Virginia. Connelly and Bair [22] developed a simulation model for an ED in Davis, California. They used the model to compare the fast-track triage approach with a proposed acuity ratio triage (ART) approach and found that the ART approach can reduce the average treatment times for high-acuity patients but increases the average service time for low-acuity patients.

Yeh and Lin [23] used simulation and genetic algorithms for nurse rostering to reduce patient waiting time in a hospital ED in Central Taiwan. Ahmed and Alkhamis [24] developed a decision support system, which integrates simulation with optimization, to determine the staffing levels of doctors, lab technicians and nurses of an ED in Kuwait. The objectives were to maximize patient throughput and to minimize patient time in the system subject to the budget constraints. The system enables the decision makers at the hospital to examine the impacts of different staffing levels on operational efficiency.

Wang et al. [25] built a simulation model for an ED in Lyon. They used the model to identify process bottlenecks and evaluate how resources allocation impacts the ED performance. Abo-Hamad and Arisha [26] developed an interactive simulation-based decision support system to help improve operations of an ED of an adult teaching hospital in North Dublin. They used the tool to examine the effects of adjusting the number of staff and the physical capacity and incorporating a ‘zero-tolerance’ policy regarding exceeding the national 6-hour boarding time. They found that the latter has a greater impact on reducing the average length of stay of patients.

All of the above examples demonstrate that simulation is an appropriate and a very powerful tool to mimic ED systems, has a wide range of applications, and can aid hospital administrators in decision making.

3. Patient Flow and Simulation Model

In this section, we describe daily operations of the ED of PWH and our simulation model.

To provide 24-hour A&E services, the ED employs different shifts of physicians to cover the patient demand over a whole day. There are mainly three shifts: morning (M), afternoon (A), and night (N). From 07:00 to 23:00, the ED is internally divided into two divisions, the Walking division and the Non-walking division, respectively treating mobile patients and patients on a trolley or wheel-chair. However, from 23:00 to 07:00, the walking patients are directed to the non-walking division and merged with the non-walking patients to receive treatments. This policy aims to well-utilize the reduced workforce commensurate with the low arrival rates of patients in nighttime.

In the ED, there are 5 categories (levels of urgency) of patients: 1 (critical), 2 (emergency), 3 (urgent), 4 (standard) and 5 (non-urgent). In our simulation and the rest of this paper, we put category 5 patients, who are only a very small portion of the overall patients, into category 4 because they have the same
flow and priority in the actual ED system. Category 1 and 2 patients have the highest priority, and
category 3 patients have a higher priority over category 4 patients. Within the same category, patients
are treated on a first-come, first-served basis. For critically ill and severely injured patients with life-
threatening condition (i.e., category 1 and 2 patients), they are usually brought by ambulances and
must be immediately sent to the resuscitation rooms and given prompt medical treatments. For the
other patients, after registration, they are examined by a triage nurse and be assigned a triage category
for prioritizing their levels of urgency. After triage, they stay in the waiting area until being called for
consultation with a physician. After consultation, some of them may receive diagnostic tests (e.g., X-
ray, blood test and CT scan), followed by a second consultation. After all the treatments are done, they
either leave PWH or are admitted to the in-patient wards.

Based on the above patient flow and the ED layout, we developed a simulation model of the ED using
simulation software ARENA. Our simulation model captures all the key treatment process (such as
triage, consultation and diagnostic tests), the complexities of intertwining and re-entrant patient flows
and time-varying and category-dependent arrival rates. The simulation model inputs include time-
varying arrival rates, probability distributions for service durations, resources and physician work
schedules. We presented our model to the senior consultant who initiated the project. He believed that
the model was sufficient to capture all the key activities and agreed with those simulated values of
KPIs. Our simulated results were also consistent with the findings in an independent research of a 5-
year study of PWH ED [27]. For more details of the development of the simulation model, further
validation and previous work, we refer the reader to [13].

4. Simulation Study: Impact of Physician Heterogeneity on Emergency Department Efficiency

In the literature on using simulation to model ED operations, most papers assume that all physicians
are homogeneous. However, in practice, this is nearly impossible. Many medical research studies
found that physician speciality has a significant impact on clinical outcomes [28, 29]. While specialists
are more knowledgeable about conditions encompassed within their speciality and are likely to use
more medical diagnostic tests and procedures to treat patients to improve clinical outcomes [30],
generalists are more efficient in the sense that they can shorten length of stay of patients [31].
Furthermore, physician experience is also another important factor in the improvement of patient
health outcomes [32]. Some recent research found that adding more junior physicians may even
worsen ED overcrowding situation [33]. All of these studies suggest that physician heterogeneity
would influence ED performance and should be considered when building simulation models.

We conduct a computational study using our simulation model to examine the impact of physician
heterogeneity on ED performance, which is one of the concerns raised by the ED. By physician
heterogeneity, we mean their efficiency and hence the service rate, which are key factors for
enhancing ED effectiveness. We use the historical data of one month provided by the ED to estimate
the patient arrival rates. The actual physician work schedule is used to set the shift times of physicians.
Because of privacy concerns, we do not use the actual service durations of individual physicians of the
ED in this experimental study. Instead, we consider three widely employed service-time distributions,
which are exponential, normal and lognormal distributions, for modelling physician consultation
durations. For normal and lognormal distributions, we set the standard deviation as a quarter of the
mean service time. For each class of distribution, we consider three different scenarios: (i)

homogeneous service rate among all physicians in the same division, (ii) heterogeneous service rates
which are equal to the rate in (i) or differ from that rate by one minute, and (iii) heterogeneous service
rates which are equal to the rate in (i) or differ from that rate by two minutes. The big changes in
service rates, in a relative sense, would allow us to observe more clearly the impact of physician
heterogeneity on ED performance. For scenarios (ii) and (iii), we set the numbers of more efficient and
less efficient physicians the same for each shift and in each division. This aims to maintain the same
average service rates among the physicians as in scenario (i). The consultation duration distributions for the nine instances are listed in Table 1.

**Table 1. Probability distributions for consultation durations.**

| Instance | Walking division | Non-walking division |
|----------|------------------|----------------------|
| Exp0     | Exp(5^a; b): M(2)^d, A(2) | Exp(12): M(4), A(4), N(3) |
| Exp1     | Exp(6): M(1), A(1) Exp(4): M(1), A(1) | Exp(13): M(2), A(2), N(1) Exp(11): M(2), A(2), N(1) Exp(12): N(1) |
| Exp2     | Exp(7): M(1), A(1) Exp(3): M(1), A(1) | Exp(14): M(2), A(2), N(1) Exp(10): M(2), A(2), N(1) Exp(12): N(1) |
| Norm0    | Norm(5^a; 1.25^b): M(2), A(2) | Norm(12, 3): M(4), A(4), N(3) |
| Norm1    | Norm(6, 1.5): M(1), A(1) Norm(4, 1): M(1), A(1) | Norm(13, 3.25): M(2), A(2), N(1) Norm(11, 2.75): M(2), A(2), N(1) Norm(12, 3): N(1) |
| Norm2    | Norm(7, 1.75): M(1), A(1) Norm(3, 0.75): M(1), A(1) | Norm(14, 3.5): M(2), A(2), N(1) Norm(10, 2.5): M(2), A(2), N(1) Norm(12, 3): N(1) |
| LogNorm0 | LogNorm(5^a; 1.25^b): M(2), A(2) | LogNorm(12, 3): M(4), A(4), N(3) |
| LogNorm1 | LogNorm(6, 1.5): M(1), A(1) LogNorm(4, 1): M(1), A(1) | LogNorm(13, 3.25): M(2), A(2), N(1) LogNorm(11, 2.75): M(2), A(2), N(1) LogNorm(12, 3): N(1) |
| LogNorm2 | LogNorm(7, 1.75): M(1), A(1) LogNorm(3, 0.75): M(1), A(1) | LogNorm(14, 3.5): M(2), A(2), N(1) LogNorm(10, 2.5): M(2), A(2), N(1) LogNorm(12, 3): N(1) |

^a Average of the distribution.
^b Standard deviation of the distribution.
^c Physician shift type.
^d Number of physicians in that shift whose consultation duration follows the corresponding distribution.

For each scenario, we ran 100 replications of simulation runs of 34 days, where each simulation replication started from an empty system. The first three days was a warm-up period and not included in our reported statistics, In other words, we simulated patient flows of 100 independent months, each starting from a non-empty system. For each instance, we generated a total number of around 1,332,000 patients (excluding those in the warm-up period) in the 100 replications. We recorded ED KPIs including the average number of patients in the ED (also known as WIP, work in process), net time for patients from registration to consultation, which we regard it as the patient waiting time (to first consultation), and physician utilization. Then we calculated their averages among the 100 replications, as reported in Table 2. Figures 1 to 4 respectively present box plots of WIP, waiting time for category 3 non-walking patients, waiting time for category 4 walking patients and physician utilization.
From Table 2, Figures 1, 3 and 4, we observe that staff heterogeneity has a significant impact on WIP, waiting time for category 4 walking patients and physician utilization. An interesting finding is that, for all the three probability-distribution classes, the average number of patients in the ED (i.e., WIP) decreases as the variation in physician service rates increases. i.e., the ED is less crowded when such variation increases. This phenomenon also appears in the columns of average waiting time for category 4 walking patients and physician utilization. The reason for having reductions in WIP and waiting time for category 4 walking patients is that, the more efficient physicians see more patients than the less efficient physicians do. As a result, the overall service rate for consultation increases as a higher weight is placed on the service rate of more efficient physicians. This speeds up the overall consultation time and thus results in fewer patients in the system and a shorter waiting time for category 4 walking patients. The physician utilization decreases as the variation in physician service rates increases because the overall consultation time is less but the patient arrival rate remains the same. However, category 3 patients and category 4 non-walking patients do not have significant change in waiting time in this experiment as they have already had a higher priority to receive consultation. Another observation is that exponential distributions appear to have higher values of those KPIs with normal and lognormal distributions of the same averages. This is because in this set of experiments exponential distributions have higher variances than normal and lognormal distributions do. A large variance in consultation duration (i.e., a higher uncertainty) would worsen the ED performance.

The computational results show that physician heterogeneity has a significant impact on ED KPIs, in particular the patients in the ED and the waiting time for patients of low priority. Therefore, individual service rates of physicians should be taken into account in order to build more accurate simulation models for EDs. The results also suggest that, with the same average service rate among physicians, variation in physician service rates can help relieve the ED overcrowding situation: the number of patients in the ED and their waiting times can be reduced. This implies that efficient physicians can compensate for more than the inefficiency caused by the less efficient physicians. Thus, to improve operational efficiency, EDs may consider having some efficient physicians to reduce the overall consultation time but at the same time having some physicians spending more time with patients who need extra medical care. However, EDs will need to think in advance about fairness issues as the efficient physicians need to see more patients and therefore have heavier workloads. If the fairness issues are not properly handled, they will lead to low morale of physicians and may even worsen the quality of medical services provided.

Table 2. Average WIP, waiting time and physician utilization.

| WIP (persons) | Waiting time (min) | Physician Utilization |
|---------------|--------------------|-----------------------|
|               | Cat. 3NW | Cat. 3W | Cat. 4NW | Cat. 4W |
| Exp0          | 77.97    | 18.03   | 26.56    | 92.03   | 281.32  | 0.93    |
| Exp1          | 67.33    | 18.03   | 27.18    | 89.36   | 215.46  | 0.92    |
| Exp2          | 51.55    | 18.04   | 26.06    | 89.36   | 117.38  | 0.88    |
| Norm0         | 68.27    | 15.09   | 25.43    | 78.51   | 234.46  | 0.93    |
| Norm1         | 58.38    | 15.15   | 25.31    | 77.91   | 169.85  | 0.91    |
| Norm2         | 46.53    | 15.16   | 25.08    | 77.1    | 95.64   | 0.87    |
| LogNorm0      | 67.12    | 15.03   | 25.14    | 77.23   | 227.04  | 0.93    |
| LogNorm1      | 59.19    | 15.35   | 25.48    | 79.5    | 174.79  | 0.91    |
| LogNorm2      | 46.05    | 14.86   | 25.39    | 74.03   | 94.24   | 0.87    |
Figure 1. Average number of patients in the ED.

Figure 2. Average waiting time for category 3 non-walking patients.
Figure 3. Average waiting time for category 4 walking patients.

Figure 4. Average physician utilization.
5. Conclusions

Overcrowding is one of the most serious and challenging issues for EDs. Both academics and practitioners have been trying different ways to resolve this phenomenon for decades but the problem remains unsolved in many EDs. In this paper, we present a case study of using simulation to analyze patient flow of a hospital ED in Hong Kong. With our simulation model, we conduct computational experiments to examine the effect of physician heterogeneity on ED performance. We found that physician heterogeneity has a significant impact on operational efficiency. Thus, individual consultation durations of physicians are crucial when building simulation models for EDs.

Computational results also show that, with the same average service rate among physicians, variation in physician service rates can improve ED overcrowding situation. This suggests that EDs may wish to have some efficient physicians who can speed up the overall consultation time in return for more time for patients who need additional care.

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