

STAFFING A PANDEMIC URGENT CARE FACILITY DURING AN OUTBREAK OF PANDEMIC INFLUENZA

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ABSTRACT

A simulation of an influenza pandemic is analyzed for the greater Ann Arbor, Michigan region. Focus is placed on a Pandemic Urgent Care center (PUC), where patients of mild and moderate severity are treated. The number of registration assistants, doctors, and nurses to staff as well as the amount of capacity to add to the PUC and adjoining infusion clinic is analyzed for different attack rates. Focus is placed on the peak day of the pandemic, and patients arrive on that day according to an empirical distribution from emergency department arrival data. ProModel is used to evaluate the system and perform sensitivity analysis. The analysis finds that the optimal staffing levels to keep average patient waiting times at a reasonable level is dependent on the attack rate and the daily interarrival rate of patients, and that more staff is needed when arrival patterns have increased variability.

1 INTRODUCTION

In the event of an outbreak of pandemic influenza, it is expected that almost 90 million people in the United States will need assistance and almost 2 million people could die (DHHS 2008a). The University of Michigan Health System (UMHS) is currently planning for such an outbreak, but has only considered deterministic models. This paper explores how UMHS' preliminary plans will react to an influenza pandemic in the greater Ann Arbor area, and aims to provide insight into the staffing levels, required resources, and problems that UMHS might encounter.

1.1 System Description

An influenza pandemic with an attack rate, or the percentage of people that contract the virus, similar to the infamous 1918-1919 pandemic is expected to result in an influx of over 200,000 people to the University of Michigan Health System over a 12-week period (see section 1.4). As a result, UMHS, as well as hospitals and planning agencies in other infected areas, will need to have a plan in place in order to treat the surge of patients in a timely fashion. Currently, UMHS plans to attempt to triage most of the infected persons by telephone to prevent infection of other individuals and smooth the patient volume. These patients will either be sent to the emergency department, an outpatient clinic, or be told to quarantine themselves at home, resulting in an opportunity for UMHS to control (via appointments) the influx of patients if they face staffing restrictions or high utilization. However, it is expected that a fair amount of patients will self-present themselves to the emergency department due to impatience or ignorance of the phone triage system.

The patients that self-present to the emergency department will arrive randomly, and pose a large potential problem for UMHS. Not only will there be a much larger volume of patients at the hospital, but the patients will also be infectious, thereby risking the health of other patients already receiving treatment for other health problems. To combat this problem, UMHS is planning to implement a "drive-thru triage system" outside the hospital, where staff will quickly inspect those infected with influenza and order the severe cases to the emergency department and all others to a Pandemic Urgent Care center (PUC) within the hospital, but separate from other units. Those admitted to the emergency department may be treated at an intensive care unit, ambulatory care center, or in the emergency room. The patients triaged to the PUC are registered, diagnosed,

and given treatment in the PUC, and then are either sent home or to an infusion clinic. Such patients (those that are sent to the PUC) are the subject of this simulation.

The PUC is currently in the planning stages – the space has been allocated for this purpose, but staffing levels, the number of beds, and supply levels have yet to be determined. This simulation focuses on the activity within the PUC because of these undetermined decision variables and due to the stochastic nature of arrivals.

1.2 Importance

The 1918-19 influenza pandemic killed 20-40 million people worldwide, which corresponded to a case-fatality rate of 2-3 percent (Patterson and Pyle 1991, Frost 1920). Hence, even though influenza pandemics are quite rare, health systems around the nation have chosen to focus some of their attention on such an event because of the potentially catastrophic results it presents. Additionally, the recent outbreak of the A(H1N1) influenza (swine flu) pandemic has reignited discussion of how to prepare and respond to a pandemic.

Currently, the University of Michigan Health System has made preliminary estimates of staffing levels and resource utilization within the Pandemic Urgent Care center using deterministic inputs; however, the addition of dynamic conditions and stochasticity allows evaluation of the system in a more believable manner, and lets the planners view the results of various decisions. This ability to perform dynamic rather than static analysis is one of the main reasons that simulation has become a popular technique in general healthcare problem solving (Eldabi, Irani, and Paul 2002). Additionally, the deterministic study forces certain assumptions that one would rather not make. For example, one has to set the doctors' utilization level at a certain rate, specify a point estimate of the average service time, and consequently calculate the number of patients the hospital can treat in a certain length of time. More importantly, the deterministic model does not explicitly address queuing, and does not incorporate any sort of arrival pattern or processing between locations (for example, it only calculates the number of patients that can be seen by a given number of doctors – it does not account for them checking in, or arriving at different points in time). However, the simulation model allows the modelers to vary the staffing levels, service times, and arrival rate of patients and evaluate the average patient idle time and staff utilization levels quickly for a wide range of input parameters, while allowing for a more realistic analysis of the system.

Careful modeling of the PUC can help UMHS make informed cost-benefit analysis decisions when planning for this treatment center, and it also has the potential to save thousands of man-hours (through staffing decisions and potential time patients would wait for treatment) and quite likely improve the quality of treatment influenza patients will receive. Additionally, this analysis can be extended by medical disaster planners in other areas.

1.3 Questions to Answer

The aim of this simulation is to evaluate the restrictions and bottlenecks at the Pandemic Urgent Care center. A primary concern is that the clinic will be under-staffed or not have enough capacity for such an influx of patients. Consequently, this analysis focuses on minimizing patient waiting times while keeping an efficient level of staff (registration staff, nurses, and doctors) at the PUC. Overstaffing at the PUC could have negative consequences because of a need to have an increased number of staff in the emergency department and outpatient clinics to treat other infected persons. Finally, estimates on the necessary capacity are needed for purchasing decisions prior to the completion of the PUC.

1.4 Assumptions

This simulation assumes that the attack rate, or the percentage of the population which contracts the pandemic within the planning horizon, is equal to 35 percent (this assumption is relaxed in Section 3.2). This value is similar to the Federal Department of Health and Human Services' estimation of past pandemic influenza attack rates. It also assumes that the length of the planning period is 12 weeks, as is commonly assumed in the academic literature and by the Centers for Disease Control and Prevention (CDC) (Rico, Salari, and Centeno 2007; DHHS 2008b).

Since the University of Michigan Health System does not have historical data on the number of patients arriving to the health system during an influenza pandemic, we consulted with UMHS officials and agreed upon the following arrival statistics: 100 percent of current UMHS patients and 10 percent of non-UMHS patients living within 40 miles of Ann Arbor, Michigan, will choose to be treated at UMHS if they contract the flu, while 27 percent of current UMHS patients and no non-UMHS patients living greater than 40 miles from Ann Arbor will choose to be treated at UMHS. Given Michigan's current demographics and the assumed attack rate of 35 percent, this results in about 258,199 infected persons potentially choosing to be serviced by UMHS over the 12-week period.

We have also assumed that the arrivals to UMHS mimic a normal distribution over the 12-week period – hence, there are low levels of arrivals that slowly increase until a peak of arrivals during the 42nd day of the period, and then arrivals slowly decrease such that the arrival distribution is symmetric (see Figure 1). While the literature contains many more complicated models of pandemic influenza’s spread (for example, see Ekici, Keskinocak, and Swann (2008) and Andersson, Bock, and Frisen (2008)), virtually all result in a bell-shaped curve. We do not develop a disease spread model because it is not the focus of this analysis. Furthermore, the Centers for Disease Control and Prevention’s FluSurge software estimates illness levels using a bell curve, and we have used the normal distribution because it is a fairly accurate representation: if anything, it will provide a conservative (high) estimate for the number of people that have the virus during the peak of the pandemic, which is the main focus of our simulation.

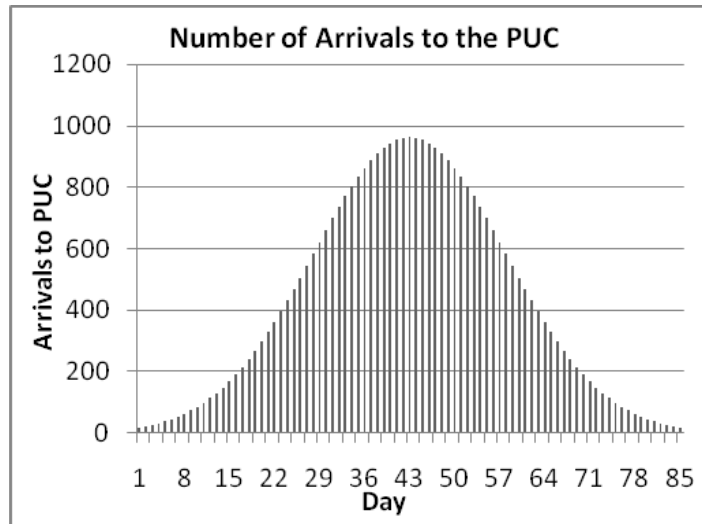


Figure 1: The arrival rate to the PUC mimics a normal distribution over a 12 week period. The number of arrivals is based on a 35 percent attack rate.

1.5 Related Literature

Numerous papers have investigated simulations of medical disasters and pandemics in general. Specific papers that investigated pandemic influenza include Lant et al. (2008), who investigate the population behaviors and effects of pandemic influenza on a public university community. Mills, Robins, and Lipsitch (2004) argues that the reproductive number (which is analogous to the attack rate) for the 1918 influenza pandemic was not large relative to many other infectious diseases, and such reproductive number estimates have been investigated in disease spread models, such as in Ekici, Keskinocak, and Swann (2008). Halloran et al. (2008) used three different models to investigate targeted layer containment strategies that might be effective in reducing transmission of pandemic influenza, such as social distancing, rapid case ascertainment, and targeted prophylaxis. Das, Savachkin, and Zhu (2008) proposed a large-scale simulation model that mimics stochastic propagation of an influenza pandemic controlled by mitigation strategies. Similarly, Flahault et al. (2006) simulates the impact of vaccination, case isolation, therapeutic and prophylactic antiviral air treatment, and air traffic reduction on the spread of an influenza pandemic within interconnected regions. Finally, Rico, Salari, and Centeno (2007) proposed a nurse allocation policy to help emergency departments minimize the number of patients waiting for treatment during a pandemic influenza outbreak. However, the literature seems to lack investigation into dedicated stand-alone centers staffed by current medical professionals within a specified region.

2 METHODS

Modeling the proposed Pandemic Urgent Care center proves difficult due to a lack of data and knowledge regarding the pandemic’s pervasiveness and spread, how infected persons will react, and processing times of patients within the PUC. In our model, we use UMHS emergency department data as well as historical and UMHS officials’ estimates to construct an expected representation of the response to an influenza pandemic.

2.1 Preliminary Plan and Triage System

In the case of a pandemic, UMHS has planned for current outpatient clinics in the greater Ann Arbor region to be transformed into similar (appointment-based) Pandemic Urgent Care centers, and plans on reorganizing staff and resources to accommodate patients at these locations. Further, special attention has been made to planning the PUC within the main hospital because of the volume of unscheduled patients that will come to this center and because the center has not been occupied, nor have staffing and resource level decisions been made.

The phone triage system will be implemented if a large-scale pandemic occurs, and the nurses staffing the phones will try to schedule patient appointments at area outpatient clinics (transformed into PUCs), send the patients to the emergency department immediately, or order them to quarantine themselves at home for a few days depending on their severity.

The drive-thru triage system will be implemented at the entrance of the hospital to triage those who do not use the phone system to either the PUC of interest or the emergency department. This type of system has not been attempted before, but hospital officials believe that it will have relative success. They plan to implement the drive-thru triage system in order to keep patients infected with influenza away from patients in the hospital who are undergoing surgery or recovering from another type of health problem.

2.2 Patient Arrivals to the Pandemic Urgent Care Center

Using the aforementioned assumptions about the number of patients entering the UMHS system over the 12-week period, UMHS officials estimate that 20 percent of influenza patients will self-present to the hospital, where they will process through the drive-thru triage system. Of the remaining 80 percent of patients, 25 percent are expected to choose not to receive service (i.e. voluntary quarantine) and 75 percent will adhere to the phone triage system.

The patients that self-present to the hospital are assumed to arrive according to a normal distribution over the 12 weeks (as discussed above). Since we are simulating over a 12-week period, we calculated the number of patients that will arrive to the PUC per day using a normal distribution with a mean of 42 days and a standard deviation of 15. A standard deviation of 15 was used because the tails of the normal distribution adequately approached zero at 0 and 84 days.

When considering how the patients will arrive to the PUC on a daily basis, we believe that the interarrival rate heavily depends on the time of day: one cannot simply assume that the arrival pattern is constant over the course of the day. Instead, we assume that the arrivals to the PUC will mirror the daily pattern of arrivals to the UMHS emergency department as both facilities are accommodating patients without scheduled appointments. Using six months of patient arrival data to the UMHS emergency department (37,949 patients), we found the daily arrival pattern is as shown in Figure 2, where patient arrivals were grouped into 30-minute increments and normalized to show the percentage of daily patients arriving by time of day.

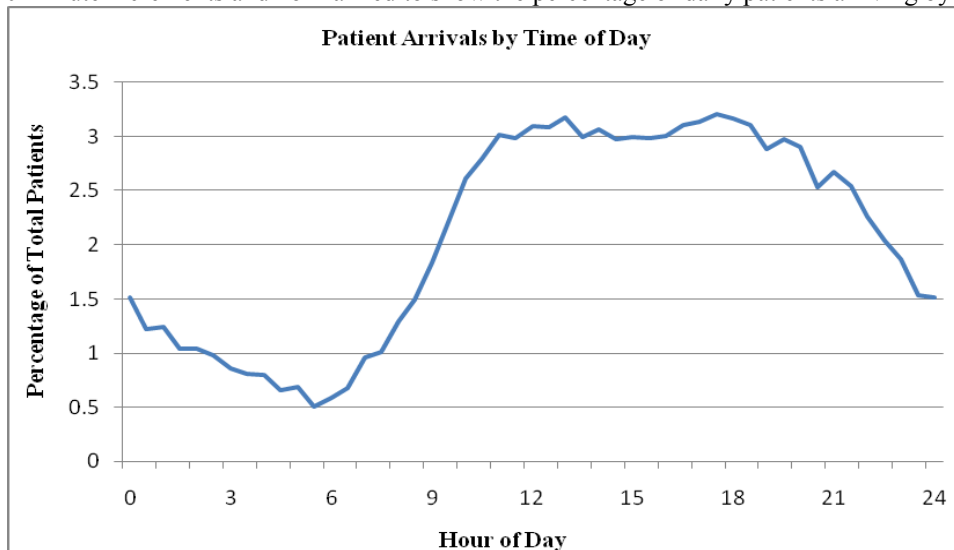


Figure 2: Percentage of total patients arriving at the emergency department by time of day (divided into 30-minute increments). The PUC is assumed to have the same arrival pattern.

Similar emergency department arrival patterns have been observed by Draeger (1992) and McCarthy et al. (2008). For a detailed analysis of how arrival rate distributions affect an emergency department's capacity see Joshi (2008). Likewise, the

number of each type of staff working at a certain time of day depends on the expected arrival pattern as well; specifically, we assume that the number of staff working between midnight and 8 AM is approximately 18 percent of the (weighted) number of people who work between 8 AM and midnight. This value was calculated using the emergency department arrival data.

2.2.1 Patient Acuity Levels

Patient acuity levels were gathered from discussions within the University of Michigan Health System and historical estimations. Given the estimate that 20 percent of influenza patients will self-present to the hospital, we expect that 30 percent of individuals that enter the drive-thru stage are immediately diagnosed as having the most severe conditions and are sent directly to the emergency department. The other 70 percent of individuals from the drive-thru clinic proceed to the PUC, where 5 percent are discovered (upon initial diagnosis and registration) to be very sick, and are sent to the emergency department instead of receiving service at the PUC. Of the remaining patients in the PUC, 80 percent are of mild severity and the other 20 percent are of moderate severity. Here, mild severity corresponds to ultimately receiving medication and being ordered home, while moderate severity will require treatment in the infusion center for dehydration and related conditions. These acuity levels produce hospitalization, intensive care unit, and mortality rates that are aligned with the CDC’s pandemic planning assumptions (DHHS 2008a).

2.3 Model Description and Structure

ProModel was used to simulate the Pandemic Urgent Care center from initial patient arrival to the PUC until the patients either were admitted to the emergency department, were sent home with medication and instructions, or completed service at the infusion clinic (see Figure 3). For clarity and simplicity, we adhere to the following terminology throughout the paper: “registration assistants/staff” refers to staff at the registration desk, “doctors” refers to those examining patients in the second stage of the simulation, and “nurses” refers to staff administering the infusion treatment. In actuality, both nurses and doctors may participate in the examination and infusion treatment processes, but the above terminology is used to avoid confusion.

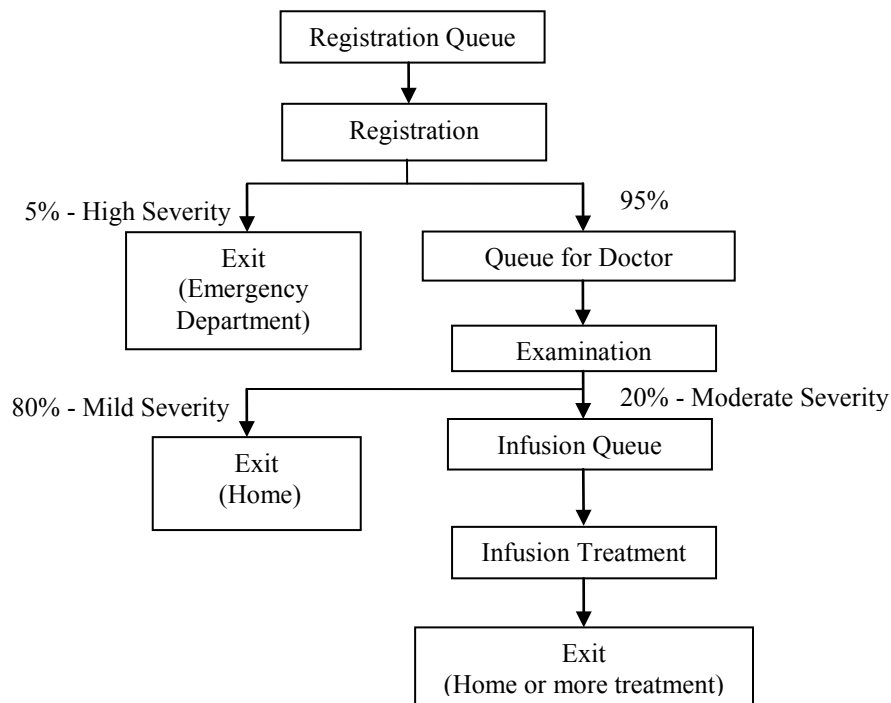


Figure 3: Flow chart representation of ProModel processing of Pandemic Urgent Care center.

First, patients arrive according to the aforementioned normal distribution (over 12 weeks), which is modeled using 85 arrival cycles corresponding to the cumulative probabilities of a normal distribution with mean 42 and standard deviation 15. When the patients arrive, they wait until they can check-in at the registration desk with the registration staff, where they fill out paperwork, process insurance information, and see if they have been previously registered in the UMHS system.

The patients are also quickly diagnosed at the check-in station, and those with the highest acuity go straight to the emergency department (as described above), while others wait to be seen by a doctor. It is of interest to note that no patient in the waiting room will be served before a patient that arrived before him, as no patient is expected to be sick enough to warrant immediate attention (or else they would have been sent to the emergency department).

Next, patients enter their own private room, where they are seen by a doctor for a stochastic amount of time which is partially determined by their acuity. The doctor diagnoses the patient and either orders the patient to go home (i.e. quarantine, if of mild severity) or proceed to the infusion treatment clinic for hydration and recuperation (if of moderate severity). If a patient has to go to the infusion clinic, they wait for an available bed. They are treated on a first-come, first-served basis, and use a nurse to set up the intravenous (IV) therapy treatment, receive the infusion treatment, and then use a nurse while they are discharged from the clinic. The input parameters for these services are given in the next section.

2.4 Input Modeling and Patient Processing

According to United States Census Bureau data, the total population of the state of Michigan is approximately 10,120,000. As mentioned above, based on geography and current provider status, UMHS has 737,710 potential patients, of which we assume 35 percent will become infected (as per the attack rate assumption). Hence, 258,199 patients are expected to arrive over the 12 week period, and are normally distributed over the 84 days.

Given UMHS estimates of 20 percent of these patients self-presenting to the emergency department (and facing the drive-thru triage system), 70 percent (or 36,148 people) will consequently enter the Pandemic Urgent Care center. The modelers and UMHS staff estimated that registration times of current UMHS and non-UMHS patients were normally distributed with parameters $N(2.5, 1.5)$ and $N(5, 2.5)$, respectively, and the percentage of patients that arrive at UMHS that were not previously UMHS patients was calculated to be 50.131 percent.

As mentioned above, it is estimated that 80 percent of patients at the PUC will be of mild severity while the other 20 percent will be of moderate severity. Since data on how long it takes a doctor to treat a patient with pandemic influenza is not readily available, doctors within UMHS have estimated that it takes, on average, 15 minutes to examine a 'mild' patient and 30 minutes to examine a 'moderate' patient. These service times were modeled as normal distributions with parameters $N(15, 2^2)$ and $N(30, 3^2)$ respectively.

Finally, UMHS doctors stated that an infusion for an influenza patient would last 150 minutes, and this value was used deterministically. Based on conversations with UMHS, the modelers estimated that a nurse would be needed for 7 minutes to set up the IV treatment, and then would be needed again for 3 minutes to discharge the patient after the treatment was finished. Appropriate downtimes were used for all staff to model scheduled breaks. The number of registration staff and doctors at the PUC, the capacity of the PUC, the number of nurses at the infusion clinic, and the number of beds at the infusion clinic were all treated as decision variables, and general estimates were provided by UMHS.

3 RESULTS

The model was validated and verified, generated acceptable results, and a sensitivity analysis was performed to compare how factors such as the attack rate, number of staff, and arrival rate distribution affect the system.

3.1 Model Output

The primary output of interest is the average idle time of the patients – the time spent waiting in the queues and waiting rooms. The average idle time of the patients is the best indication of the inefficiencies of the system, provided that more resources can be added if idle times are sufficiently long. This is because whenever a patient is checking in, being diagnosed by a doctor, or receiving infusion treatment, they are receiving the service they needed when they arrived at the clinic. However, any waiting times at the registration desk, the waiting area for the doctors, or the waiting area for a bed to receive intravenous therapy is time that the patient could be becoming sicker, or time that the patient could have been contributing to society if they were treated earlier. Subsequently, the number of registration staff, doctors, and nurses were varied from the original estimates obtained from UMHS officials to perform a sensitivity analysis.

3.2 Output Analysis

The system was first analyzed by simulating the entire 12-week period. The number of examination rooms and infusion beds were set at 25 and 30 respectively, and these estimates were approved by the planners. It is of interest to note that these values do not play a primary role in our analysis – as long as the number of doctors and nurses, respectively, do not exceed these

values, our result is feasible. Instead, we will focus on how many registration staff, doctors, and nurses to staff. The number of doctors (concurrently) working between 8 AM and midnight and from midnight to 8 AM were set at 13 and 3, respectively. The number of registration staff working between 8 AM and midnight and from midnight to 8 AM were set at 5 and 1, respectively, and the number of nurses working between those times were set at 8 and 2, respectively. These initial estimates were confirmed to be valid by a UMHS official. (Hereafter, we will only report the number of each type of staff working during peak hours (from 8 AM to midnight); the number working from midnight to 8 AM can be found by multiplying the number of staff by 0.1817 and then rounding the value up to the next highest integer – we would rather have extra staff working during off-peak hours, especially because the number working during the off-peak hours is relatively low to begin with.) Analysis of the system over the 12-week period showed relatively low utilization and queue levels, as the low arrival rates at the beginning and end of the period counteracted the high levels from the middle of the 12-week period.

To analyze the system at its most extreme condition, we then simulated the PUC for the busiest day of the 12-week period – day 42, where 962 people are expected to visit the PUC. First, we modeled these patients as arriving according to a Poisson process over the 24-hour period in order to determine how long of a warm-up period was needed until the simulation reached steady-state. Using a periodic batch mean method with 30 minute intervals and 20 replications, we found that the simulation had an initialization bias of approximately three hours. This was expected, as increased queuing would not occur until patients began to occupy the doctors’ examination rooms and the infusion clinic. We use a warm-up period of three hours for the remaining analysis because we assume that the PUC will remain open for 24 hours per day, so the system will be at steady-state when we begin the simulation of the peak day.

The performance criterion by which we make staffing decisions for this analysis is the average patient idle time, or the average time a patient waits to be served at the registration desk, waits for a doctor to see him/her, and waits before infusion treatment begins (if necessary). To the best of our knowledge, a set goal for the average patient idle time in an urgent care center or emergency department has not been agreed upon. After consultation with various UMHS officials, we agreed that an average patient idle time goal of 30 minutes is reasonable. In comparison, a National Health Statistics report found that approximately 62 percent of emergency room wait times are less than 60 minutes (Pitts et al. 2008). Although our goal of 30 minutes would be aggressive for an emergency department, we believe that it is achievable for the PUC because of the relatively short examination times and ease and uniformity of treatment.

In order to find the staffing levels to achieve the 30 minute idle time goal, we first used arrival cycles in ProModel to implement the daily arrival pattern described above (and displayed in Figure 2). Using the 35 percent attack rate assumption, we performed a sensitivity analysis to find the bottleneck in the PUC and subsequently determine optimal staffing levels. It was immediately evident that the infusion clinic was not a bottleneck because only 20 percent of patients were sent to the clinic, and nurses only had to attend to the patients at the beginning and end of their treatment. Consequently, we determined that UMHS’ plan of staffing 8 nurses during the peak period and having 30 infusion clinic beds was sufficient.

The number of registration staff and the number of doctors were then varied and the 95 percent confidence intervals for the average patient idle time were recorded for appropriate combinations of staff, which are shown in Table 1. The analysis found that at least 6 registration staff are needed to keep the average idle time acceptable (the significant change in average idle time between having 5 and 6 registration staff is mostly due to the fact that only 1 registration staff member works in off-peak hours when 5 work during peak hours, but 2 work in off-peak hours if 6 work during peak hours). However, employing more than 6 registration staff was found to have a statistically insignificant effect on the system, as the 95% confidence intervals of greater than 6 staff members for a given number of doctors overlapped with the 95% confidence intervals with 6 registration staff members. With 6 registration assistants, UMHS should employ 19 or 20 doctors per shift to keep the average patient idle time close to the desired 30-minute goal.

Table 1: 95% confidence intervals for the average patient idle time (in minutes) for a given number of doctors and registration staff, given 962 patients arrive in one day according to the emergency department arrival distribution (35% attack rate).

		Number of Doctors (Peak Hours)				
		17	18	19	20	21
Number of Registration Staff (Peak Hours)	5	(144.9, 178.2)	(135.1, 172.2)	(122.3, 154.2)	(127.5, 161.5)	(111.9, 140.1)
	6	(41.2, 51.1)	(33.8, 39.4)	(30.8, 34.7)	(29.7, 33.8)	(30.0, 33.7)
	7	(38.9, 47.0)	(32.9, 38.8)	(31.5, 35.2)	(29.3, 33.4)	(28.6, 32.5)
	8	(39.4, 47.8)	(31.2, 37.6)	(29.5, 34.5)	(30.3, 34.3)	(31.1, 35.7)
	9	(41.8, 50.8)	(34.3, 42.4)	(31.2, 35.8)	(28.6, 32.6)	(29.9, 34.2)

This analysis assumes that the attack rate of the influenza pandemic is 35 percent, which is considered an aggressive estimate. In order to investigate the effect a lower attack rate has on the staffing decisions, we performed the same simulation

with an attack rate of 20 percent. With this attack rate, 550 patients are expected to arrive at the PUC during day 42, as opposed to the 962 people from the 35 percent attack rate case. In this case, UMHS should employ 12 doctors and 3 registration staff during the peak hours in order to achieve the average patient idle time goal of 30 minutes. The results for this 20 percent attack rate case are summarized in Table 2 and displayed in Figure 4.

Table 2: 95% confidence intervals for the average patient idle time (minutes) for a given number of doctors and registration staff, given 550 patients arrive in one day according to the emergency department arrival distribution (20% attack rate).

		Number of Doctors (Peak Hours)		
		10	11	12
Number of Registration Staff (Peak Hours)	2	(86, 96)	(80, 89)	(60, 68)
	3	(45, 55)	(39, 43)	(10, 14)
	4	(45, 58)	(40, 44)	(10, 14)
	5	(44, 51)	(39, 42)	(9, 13)
	6	(42, 56)	(38, 41)	(9, 12)

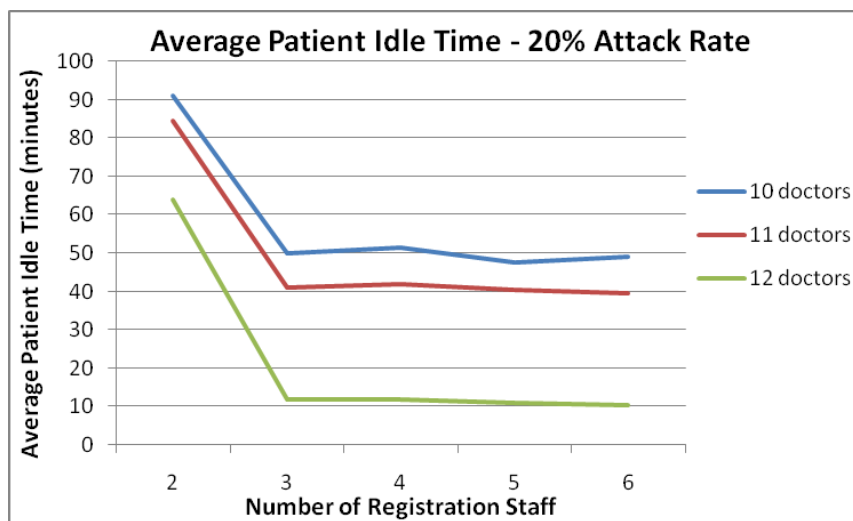


Figure 4: Mean average patient idle time as a function of the number of registration staff and doctors (20% attack rate case).

The large reduction in average patient idle time when employing 3 registration staff as compared to 2 shows that if 2 registration assistants are employed the registration assistants can be considered the bottleneck. If more than 2 registration assistants are employed, the number of doctors working during off-peak hours is the largest contributor of the difference between idle times when 11 versus 12 doctors are employed during peak hours – when 11 doctors are employed during peak hours, 2 doctors are employed during off-peak hours, as opposed to 3 off-peak doctors if 12 work during peak hours. Additionally, if the same number of staff were employed as in the 35 percent attack rate case, waiting times would be negligible.

The above analysis has assumed that both the phone triage system and the drive-thru triage system will be successful in diagnosing patients and directing them to the location appropriate for their acuity (and scheduling appointments in outpatient clinics in the case of the phone triage system). However, neither approach has been employed by UMHS before, so it is appropriate to analyze how the PUC will perform if the triage system does not perform as expected. To this end, we simulated the PUC assuming that the drive-thru triage system did not exist – we assume that all patients that arrive at the hospital without an appointment are sent directly to the PUC. In comparison, this situation is analogous to approximately 14 percent of patients that *would* have been triaged via phone choosing to go to the hospital instead (and be subjected to the drive-thru triage), or the same as the pandemic having a 50 percent attack rate.

In this scenario, 51,640 patients are expected to be seen at the PUC over the 12-week period, with 1374 patients arriving during the peak day. For this case, we found that it is optimal for UMHS to employ 6 registration assistants and 34 doctors during the peak hours to achieve the 30-minute average idle time goal. It is important to note that the initial examination room capacity (and hence the ‘cap’ on the number of doctors that can work at one point in time) was chosen to be 25 rooms. With this patient level and 30-minute average idle time goal, at least 9 more examination rooms would need to be added to the PUC. If only 25 doctors could be employed during the peak hours, the average waiting time would exceed 60 minutes.

Finally, in order to analyze how the daily arrival pattern affects the staffing decisions, we simulated the PUC assuming a 35 percent attack rate and that patients arrived according to a Poisson process with rate 0.668 patients/minute (i.e., 962 patients are expected to arrive over the 24-hour period). Here, the number of staff working during off-peak and peak hours is assumed to be the same, as the rate of arrivals is constant over the course of the day. Consequently, we found that 5 registration assistants and 12 doctors are needed to achieve the 30-minute idle time goal, whereas above we found that 6 registration assistants during peak hours (2 during off-peak hours) and 19 or 20 doctors during peak hours (4 during off-peak hours) are needed if patients arrive according to the emergency department arrival pattern. To view the consequences of the daily arrival pattern in another light, note that only 8 more registration staff-hours but at least 48 less doctor-hours are needed in the Poisson arrivals case. This shows that an increase in the variability of the arrival rate leads to longer expected waiting times for a given number of staff.

3.3 Model Validation and Verification

Methods discussed in Sargent (2004) were used for validation and verification of the model. First, the assumptions of the model were validated through iterations of conversations with various UMHS officials and confirmation with the academic literature and statements by the CDC. Assumptions about the form of the data were also validated in a similar manner – the reliability of the data was verified by consultation with a UMHS official, and some data was confirmed in other studies.

The model also has face validity, as the model's output was reasonable when the input parameters were varied during the sensitivity analysis. For example, when the number of staff (especially registration staff or doctors) is increased, average idle times decrease. Additionally, if service times are increased or a greater proportion of patients have a moderate (rather than mild) acuity, the average time a patient spends in the system increases.

The model has been structurally validated, as a UMHS official approved the processing and layout of the system. Finally, the output data generally agrees with results generated from UMHS' deterministic analysis of the possible system. Although the deterministic analysis disregards a lot of factors (as described in the first section), it determined that 15 doctors (with a utilization level of 95 percent) could treat 882 patients in a 24-hour period, whereas our simulation found that 12 doctors were needed to treat 962 patients arriving according to a Poisson process in the same length of time. We believe that the difference is partly because our analysis incorporates queueing – in fact, the average time spent in the queue is approximately 30 minutes – and other processing while the deterministic model does not.

4 DISCUSSION

Although planning for an influenza pandemic poses to be a challenging problem with a lack of significant historical data, this simulation has produced helpful and reasonable results using available data and expert estimations on necessary information.

4.1 Conclusions

The results of the simulation are well-aligned with what one would most likely expect. We find that the optimal staffing levels are heavily dependent on the distribution of arrivals over the course of the day and the attack rate of the pandemic. Although staffing decisions are not as important at the beginning or end of the pandemic because fewer patients will arrive to the PUC, they are integral in keeping average patient idle time at a reasonable level when the busy period occurs.

Consequently, in the event of an influenza pandemic, UMHS should take initial data on the daily arrival distribution while the number of arrivals is low to have the optimal number of staff in place when the busy period occurs. We believe that the empirical arrival distribution will fit the PUC's arrival data fairly well, and certainly much better than modeling the arrivals as a Poisson process. Hence, for the case of a 35 percent attack rate, the bottleneck seems to primarily be the doctors as long as 6 registration assistants are employed during peak hours. In order to verify if the staffing levels suggested by our analysis are economically viable, cost-benefit analysis should be performed. We also anticipate that UMHS will lean towards adding registration assistants rather than doctors if both will lead to the similar results, as assistants require less financial resources and are expected to be easier to hire and train; however, we found that employing more than 6 registration assistants at the 35 percent attack rate has a statistically insignificant effect on average patient idle time. Additionally, we discovered that the total number of staff hours needed for the empirical arrival pattern case is higher than the exponential arrival case, which should be taken into account after arrivals are observed during the beginning of the pandemic. In some cases we also found that number of staff working during off-peak hours affects the average patient idle time more than the number working during peak hours – in this case, UMHS can consider increasing the number working during off-peak hours without adjusting other staffing levels.

In addition, this analysis was performed assuming that the number of infected persons mimics a normal distribution over the 12-week period. Although large-scale planning will depend on this assumption, daily staffing decisions are only dependent on the expected number of patients that will arrive. Consequently, the results from this analysis are still valuable for short-term decisions even if the disease spreads differently.

Finally, this system was analyzed assuming that 60 percent of patients are triaged via telephone (and are subsequently sent to either the emergency department or an outpatient clinic) and 20 percent of patients choose to stay home until they recover. If the phone triage process does not work well or if the phone lines become congested, more patients will choose to self-present themselves to the hospital and end up at the PUC. Additionally, if the drive-thru triage system does a poor job of diagnosing patients – which seems plausible, as nurses have never tried to diagnose patients while the patients are in their vehicles in the parking lot – then it is likely that more patients will be sent to the PUC for further examination. Both of these scenarios will result in an even greater influx of patients to the PUC (one such case is analyzed in section 3.2), and staffing and resource levels will have to be subsequently increased, or patient idle times will increase.

4.2 Recommendations

We recommend that UMHS focuses on the bottleneck of the system – specifically, the doctors within the PUC. Many doctors will be needed in the greater Ann Arbor area in the event of an influenza pandemic, so care should be taken to employ a reasonable amount of doctors for the PUC – overstaffing might result in shortages at other locations. We also found that registration assistants were the second-most sensitive factor for our analysis and that a threshold existed for the number of registration staff needed, and the estimate of nurses given by UMHS was more than adequate. In section 3.2, we determined the number of staff to employ under the arrival rate scenarios to keep the average patient idle time close to 30 minutes, which the authors believe is a reasonable goal. However, UMHS will need to perform cost-benefit analysis to find what staffing levels are ultimately best for them.

One should also be aware that there might be an increased need for staff and medical resources if the phone triage or drive-thru triage is not effective. Considering that neither of these systems have been implemented at UMHS before, the success that these systems will have is fairly unknown. If either system performs below expectations, UMHS should be prepared for an increase in the volume of patients the PUC has to treat.

Finally, while these results are reasonable, validated, and fit with the deterministic analysis, caution should be used when implementing measures based on these results. Although we believe this analysis is accurate, it is based on values and assumptions from the academic literature, the Centers for Disease Control and Prevention, and data and expert opinions from UMHS. This information may not represent the outcomes of a specific pandemic that may occur in the future. Precautions should be taken to be prepared (and have a back-up plan) for alternative scenarios.

4.3 Implementation Possibilities and Overall Importance

The results of this model can be used for decisions by UMHS about the staffing of a newly-created Pandemic Urgent Care center within the main hospital as well as an infusion clinic attached to the PUC. Additionally, UMHS can use this information to make informed decisions about how many medical resources should be purchased and how much capacity is needed for the peak of a pandemic. The framework of this model can also be used to evaluate policies for other types of pandemics and medical disasters, and provides a starting point for other health systems to analyze their plan for a similar pandemic.

Although influenza pandemics are rare, the devastation that is caused when one occurs warrants the effort of taking precautionary measures and formulating hypothetical plans of how to handle the treatment of infected individuals. Diligent planning and analysis can literally help save or influence thousands of lives in the event of pandemic influenza.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to Paul Paliani, Sam Clark, Carrie Wright, and the University of Michigan Health System as a whole for helping us understand their current plans, as well as for providing information on the data and assumptions needed to produce this simulation. We also appreciate invaluable editorial comments from Erdem Eskigun and two anonymous referees.

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