

Montgomery County's Public Health Service Uses Operations Research to Plan Emergency Mass Dispensing and Vaccination Clinics

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To curb outbreaks of contagious diseases, county health departments must set up and operate clinics to dispense medications and vaccines. Carefully planning these clinics in advance of such an event is difficult and important. We developed and implemented operations research models to improve clinic planning for the Montgomery County (Maryland) Public Health Services. They include discrete-event simulation models and capacity-planning and queueing-system models. We validated these models using data that we collected during full-scale simulations of disease outbreaks. We also developed guidelines for the physical design of clinics based on general queueing principles and our own experiences.

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The threat of an outbreak of contagious disease in the United States, caused by a terrorist act or a natural occurrence, has prompted public health departments to update and enhance their plans for responding to such events. Especially in regions that are densely populated or strategically important, such as the nation's capital, public health officials must plan for potential disasters. In the worst-case scenario, terrorists could release a lethal virus, such as smallpox, into the general population. If this were to happen, every person in the affected area would

have to be vaccinated within a few days. For example, Montgomery County, Maryland, would need to vaccinate nearly one million people. To vaccinate so many people in a short period, it would have to set up mass-vaccination clinics at designated sites throughout the county. Kaplan et al. (2002) compare vaccination policies for responding to a smallpox attack and show that mass vaccination results in many fewer deaths than other tactics in the most likely attack scenarios. The spread of a pandemic flu could also trigger mass vaccinations.

Carefully planning mass-dispensing and vaccination clinics (or points of dispensing (PODs)) is important. The health department must train the right number of people beforehand (although they can do some training at the time of need), and must assign the right number of workers to various roles when the clinic begins operations. They must consider the capacity of each clinic (the number of residents it can serve per hour) and the number of minutes residents would spend in the clinic (the time in system, the flow time, or the throughput time). Clinic capacity affects the number of clinics needed and the total time needed to vaccinate the affected population. The time in system affects the number of residents who would be inside the clinic waiting for treatment; too many residents in the clinic can cause crowding and confusion.

The Centers for Disease Control and Prevention (CDC) (2002) have created guidelines to help county health departments plan their responses to such incidents. The guidelines provide some estimates of the time needed to perform such activities and, based on these estimates, suggest the number of staff needed to meet a specific throughput target (118,000 residents per day in Montgomery County). One purpose of our research was to acquire further data about realistic processing times and to assess the adequacy of the existing guidelines.

Clinic capacity and time in system are not the only concerns in planning such clinics. Based on mass-prophylaxis operations in 2001, Blank et al. (2003) described practical concerns that arise in planning and operating mass-dispensing and vaccination clinics, issues (including the incident command system) similar to those faced by managers preparing for other health-care emergency situations (Gardner 1999).

Researchers have used simulation modeling to model health-care systems, such as medical centers, hospitals, and clinical practices (Ledlow and Bradshaw 1999, Merkle 2002, Prieditis et al. 2005, Swisher and Jacobson 2002, Su et al. 2005). Other formal techniques have been applied as well: Malakooti (2004) used a cell-formation approach to design emergency rooms, and Jain and McLean (2004) describe a framework for linking simulation models of disasters.

We developed discrete-event simulation models and capacity-planning and queueing-system models

to improve clinic planning in an ongoing collaboration between the University of Maryland, College Park, and the Montgomery County Public Health Services (PHS).

Planning Mass-Dispensing and Vaccination Clinics

Prior to September 11, 2001, Montgomery County, Maryland, had no plans for mass-dispensing and vaccination clinics. PHS, a division of the county's health and human services department, conducted small-scale clinics for county residents, for example, to administer flu vaccine or conduct tuberculosis screening. The importance of mass-dispensing became clear after the anthrax attacks in October 2001. PHS dispensed oral medications through mass-dispensing clinics to postal workers and others who may have been exposed to anthrax. These clinics were quite small (treating about 1,400 residents) and were easy to manage based on the county's previous experience with flu vaccination clinics. In 2002, the CDC began requiring public health departments to develop smallpox vaccination plans. PHS developed those plans to meet CDC and state guidelines. The CDC implemented guidelines for operating dispensing and vaccination clinics, which allowed PHS to enhance their clinic plans. In addition, the county added operational detail to its plans to achieve the Public Health Ready designation defined by the National Association of County and City Health Officials (NACCHO). For a site to earn Public Health Ready status, it must meet goals in three areas: emergency preparedness and response planning, workforce competency development, and exercise simulations (NACCHO 2005b). NACCHO evaluators look for plan components, including a concept of operations, detailed descriptions of staff roles, training plans for staff, and reports on exercises that have been conducted.

In June 2004, PHS tested its plans for smallpox clinics by simulating a mock vaccination clinic in a full-scale exercise and conducting a time study of the residents going through the clinic. The results showed that PHS needed to strengthen two areas: the logistics of setting up a clinic and improving the clinic-flow patterns. PHS had an opportunity to test its updated procedures for clinic setup during the January 2005

swearing-in of President Bush, when the State of Maryland requested Montgomery County to have a POD available in case of emergency. The model built on the smallpox time study validated the county's plans and helped it to correct the clinic layout and to assign staff.

Although each county has its own plan for setting up and operating a clinic, a typical vaccination clinic is based upon CDC guidelines, and county health departments in addition to Montgomery's are planning to use the following type of clinic:

After gathering at staging areas, residents travel on school buses to the clinic. Using media channels, the PHS advises those with smallpox symptoms to go to the nearest hospital for treatment, not to the vaccination clinics. The building housing the clinic may be a school, a recreation center, a concert hall, or some other facility that can handle a large number of people. Clinics are not located in medical facilities because those facilities will be extremely busy during an event.

At the clinic, residents go to the triage station outside the clinic building. Members of the triage station staff ask residents whether they have any symptoms of smallpox (a rash or fever) or know they have been exposed to the smallpox virus. Other staff members escort symptomatic residents to a symptoms room, where they will consult a doctor. Residents exposed to the virus go to a holding room to wait for medical attention. After consulting a doctor, infected residents exit the clinic and go to the hospital; healthy residents are allowed continue to registration (Figure 1).

After entering the clinic, residents obtain registration forms and printed information on smallpox at the registration station. (The staff includes translators.) Residents then go to the education station, classrooms in which they watch informational videos about the smallpox vaccine and fill in the registration forms. (Some classrooms will show a Spanish-language version of the video.) The education station staff manages the classrooms and checks the registration forms for completeness. Residents then walk to the screening station.

At the screening station, they see medical personnel who check their registration forms and direct residents with possible complications based on their medical histories to visit the consultation station. The remaining residents sign consent forms and go directly to the vaccination station.

At the consultation station, residents discuss possible complications with a doctor. Those who refuse the vaccination receive an information sheet and leave the clinic. They will be monitored by public health officials. Those who decide to be vaccinated sign consent forms and go to the vaccination station.

At the vaccination station, a vaccination nurse verifies that the consent form has been signed and witnessed and then vaccinates the resident. Another staff member and the resident go over an information sheet about what to do after the vaccination, and then the resident leaves the clinic.

Clinic Simulation Models

We began our analysis of clinic planning with a simulation study to evaluate alternative clinic designs (Aaby et al. 2005). We limited the scope of the simulation study to clinic operations and two key performance measures, capacity and time in system. We did not consider transporting people to the clinic or handling vaccines and other supplies. For data, we relied on a time study of a mass-vaccination clinic simulated on June 21, 2004 by the Montgomery County PHS. PHS conducted a trial run of the emergency procedures it would use for mass vaccination in the event of a widespread outbreak of smallpox. It opened the clinic in a high school in Silver Spring, Maryland, with nurses at the vaccination station simulating the smallpox vaccination step by poking residents' arms with coffee stirrers.

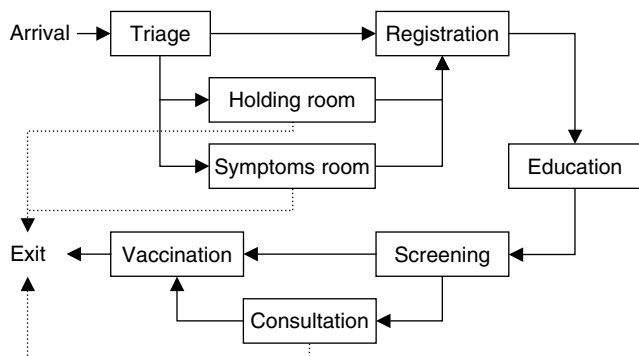


Figure 1: In this flowchart of resident flow, the dashed lines show residents who exit without receiving vaccinations.

In this full-scale exercise, 152 workers and volunteers formed the professional, command, and administrative staff, and volunteers from the local workforce and community served as residents. We encouraged county workers, especially PHS staff members, to participate with their families as volunteers. The volunteers included elderly people, children, and individuals with physical disabilities. A local newspaper covered the exercise (Harvey 2004).

Approximately 530 people participated in the exercise as residents during a two-and-a-half hour period. Researchers from the University of Maryland, along with student volunteers, conducted a time study to collect data on clinic performance during the exercise. We gave residents time-stamp forms on arrival stamped with the time (hour and minute) of their arrival, and as they walked through the clinic from station to station, they received time stamps at tables. We collected the forms at the last time-stamp table. We used electronic timers to give the time stamps and video cameras to record the processes at each station. We watched the videos to get data on stations outside of the main clinic flow, where time stamps were not given. The time study team also collected data on bus arrivals, noting the times of arrival and the number of residents on each bus. The average arrival rate was 213 residents per hour. In analyzing the data collected, we estimated how long residents spent at each station, the total time in the clinic, and the distributions of the processing time at each station (Table 1).

We designed and built a discrete-event simulation model of the mass-vaccination clinic using Rockwell

Station	Measured from exercise (minutes)	Given in CDC guidelines (minutes)
Triage	0.267	1.0
Registration	0.117	0.5 to 2
Education	22.117	30
Screening	1.717	5 to 10
Consultation	3.7	5 to 15
Vaccination	3.6	0.5 to 2
Symptoms	1.2	10
Contacts	3.8	10

Table 1: We determined the mean processing times from the data that was collected during the exercise; some times differ greatly from the guidelines suggested by the CDC.

Software's Arena 5.00. For validation purposes, we designed the initial model to simulate the exercise we had conducted. Residents arrived in batches that corresponded to the actual bus arrivals. In the model, we represented residents as entities that progressed through different queues and processes. The model included animation allowing the user to visualize the movement of residents through the clinic. We compared the results we obtained from the simulation for average station cycle time to the data collected in the exercise (Figure 2). Although the measured and simulated times are not as close as desired, we found the simulation model acceptable as a valid representation of the real clinic.

After validating the model with our results, we used simulation to evaluate alternative clinic designs and operational policies. The first factor we studied was the distribution of bus interarrival times.

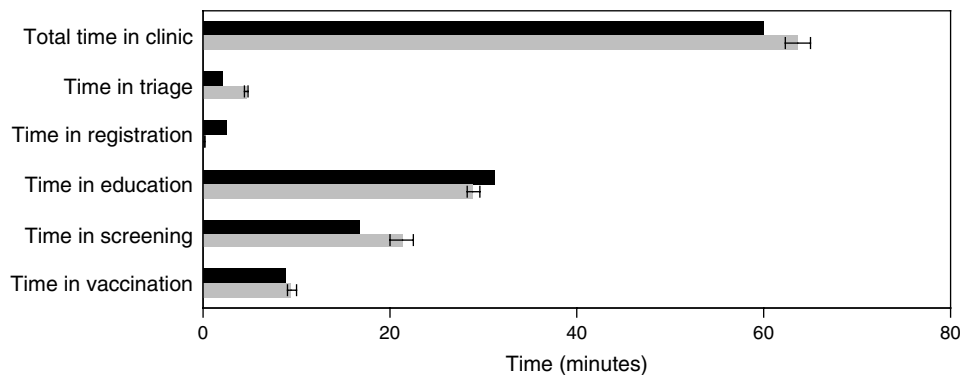


Figure 2: The validation results show the average time that a resident spent at each station and the total time (in minutes) measured at the exercise (black bars) and from the results of the simulation study (gray bars). The simulation results have error bars corresponding to the 95 percent confidence intervals.

We conducted experiments to quantify the impact of arrival variability, measured by the squared coefficient of variation (SCV). We used the following interarrival time distributions: exponential (SCV = 1), gamma (SCV = 0.25), and constant (SCV = 0) (Figure 3). We found that the variability in bus interarrival times caused congestion. Clinic managers can control bus arrivals by improving the dispatching of buses from the staging areas.

We also considered reducing the batch sizes at the education station (by cutting the number of residents per classroom), along with reducing the number of registration and screening staff. We must group people for education because we have a limited number of TVs available, even though doing so causes delays in the clinic. Reducing this batch size should reduce congestion, while increasing it should increase congestion. However, the simulation results showed that changing classroom size to 20 or 40 did not reduce time in the clinic significantly at the highest arrival rates (Figure 4).

In the baseline model, the utilization of the screening staff is at most 52 percent, and the utilization of the registration staff is at most seven percent, indicating that too many staff members are working at these stations. Reducing their numbers at these stations should increase congestion slightly. To evaluate

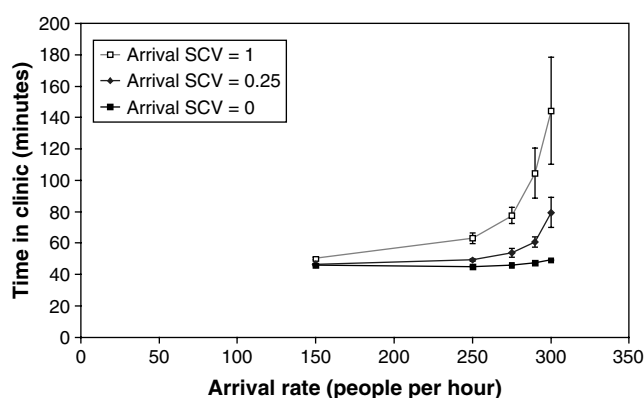


Figure 3: We compared the average total time in the clinic to the arrival rate for several distributions of bus interarrival times. Hollow squares correspond to the exponential distribution, diamonds to a gamma distribution, and filled squares to constant interarrival times. Error bars represent the 95 percent confidence interval of the simulation results. It is readily apparent that interarrival variability has a large impact on the time in the clinic.

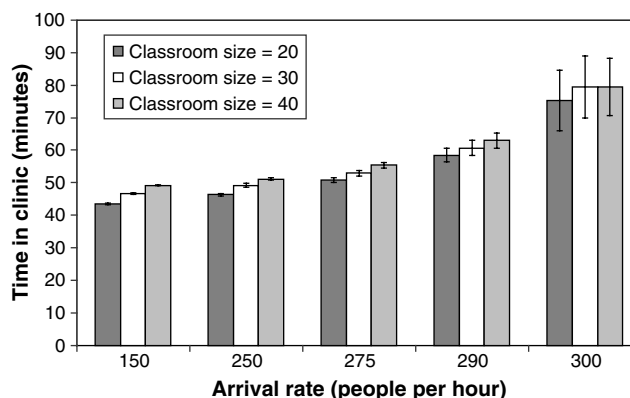


Figure 4: The average total time in the clinic does not change significantly with different classroom batch sizes, even at the highest rates of resident arrivals.

the impact, we created a reduced staffing model with only 10 members of the screening staff (instead of 16) and one member of the registration staff (instead of nine). At the highest arrival rate, the utilization of the screening staff increased to 84 percent; that of the registration staff to 59 percent. The increase in time in the clinic was not significant; at the highest arrival rate, the time in the system was 80.4 minutes (with a 95 percent confidence interval half-width of 9.3 minutes). Thus, the clinic could reduce its staff by 14 staff members with little increase in congestion and still maintain the same clinic capacity.

Capacity-Planning and Queueing Models

Discrete-event simulation models, although very useful, require specialized software that public health officials do not have. Thus, we developed capacity-planning and queueing models using spreadsheet software that is commonly available.

We wanted to provide public health officials with accurate models for planning mass-dispensing or vaccination campaigns. Clinic planners can use the models to answer the following questions:

- (1) Given a resident flow rate (calculated from population size and duration of campaign), how many people do we need to staff each station?
- (2) How much does each work station need to accommodate residents waiting in line?
- (3) How long will residents spend inside the clinic?

(4) How will the clinic's operations be affected if stations are eliminated or combined?

We originally developed two capacity-planning and queueing models: one for vaccination against a contagious disease, such as smallpox (based on the configuration in Figure 1), and another for dispensing medicine (such as antibiotics in case of anthrax). Based on feedback from public health officials, who felt that these two models did not offer sufficient flexibility, we created software that can generate a spreadsheet-based capacity-planning and queueing model for a customized clinic configuration. Public health officials need to create models for a wide range of clinic designs to plan for new emergencies, such as pandemic flu (Aaby et al. 2006).

The model allows clinic planners to enter known population information and set time constraints specific to their applications (Figure 5). The immediate results include the minimum staff levels required, along with detailed clinic information regarding waiting times, queue lengths, and cycle time. Planners can easily adjust staffing levels and various inputs until they are satisfied with the efficiency of the clinics. Users can accept default values if they have little information about their clinics, or input more detailed information, such as routing probabilities and process times.

Because no resident visits every station, clinic capacity is not simply the minimum station capacity. Based on the routing probabilities, the capacity-planning and queueing models estimate the number of residents (as a percentage of the total) that each station will serve and use this number to find each station's constraint (upper bound) on the clinic capacity. The minimum of these is the clinic capacity (Table 2) (Appendix).

In addition to capacity, the average total time in the clinic, the average time at each work station, and the average number of residents waiting in line at each work station are important clinic performance measures. To estimate these quantities, we modeled the clinic as an open queueing network and decomposed the network by estimating the performance of each work station using a combination of queueing approximations (Appendix). Many software packages for analyzing queueing networks are available, but public health officials do not have access to them. Including

the required mathematical analysis in the spreadsheet-based capacity-planning and queueing models simplifies their use of the models.

It has not been feasible to compare the results of the capacity-planning and queueing model to the actual clinic performance because the model estimates the clinic's steady-state performance. However, the PHS has conducted only limited exercises, so we have no actual steady-state performance available.

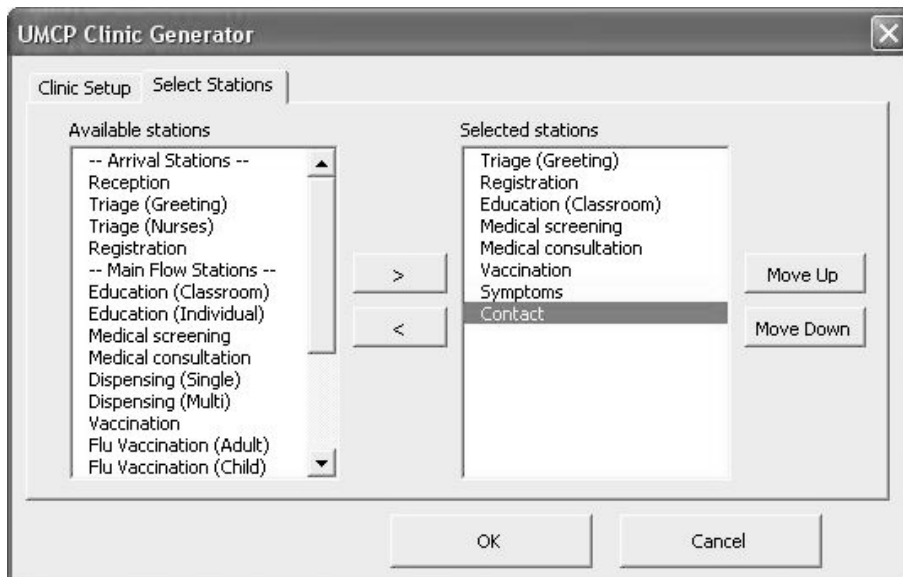
We conducted a computational study to compare the results of the capacity-planning and queueing model to those from a simulation model of the steady-state performance of a clinic. The errors were small, although slightly larger than the confidence intervals on the simulation results (Treadwell and Herrmann 2005). The capacity-planning and queueing model provides estimates that are as close as those provided by other queueing software. Our spreadsheet-based model helps clinic planners and managers to quickly estimate clinic capacity and congestion as an event unfolds without waiting for long simulation runs to be completed.

Layout and Operational Guidelines

Our models quantitatively assess a clinic design based on the key performance measures of capacity and time in system. To plan a clinic, public health officials must make many detailed design decisions, especially regarding layout. Because they will set up clinics in existing facilities of various shapes and sizes, it would not be useful for us to provide a detailed layout for a complete clinic. Instead, we developed guidelines that planners can use. We based some of them on general queue-design knowledge, including Hall's (1991) ideas, while others are specific to mass-dispensing and vaccination clinics. We grouped layout and operational guidelines into four categories: clinic layout, clinic operations, work-station layout, and work-station operations.

Clinic Layout

Our guidelines for the overall layout of the clinic and the location of work stations include the following: Have a separate entrance for staff. Triage residents outside the clinic. Protect residents waiting outside from the weather. Place easy-to-understand signs where residents can see them as they move through



Inputs			Outputs			
Demand			General performance			
Size of population to be treated:	50,000		Time in clinic (min):	78.37		
Time allotted for treatment (days):	10		Average number of patients in clinic:	82		
Daily hours of operation:	16		Bus interarrival time (min):	28.80		
Number of clinic sites:	5		Clinic capacity (patients per hour):	68		
Required throughput (patients per hour):	63		Total staff per shift across all clinics:	195		
Staffing (per clinic site)			Station-level results			
Station name	Staff per shift	Minimum staff per shift	Station name	Wait time (min)	Queue length	Utilization
Reception	2	2	Reception	22.32	14	64.4%
Triage (Greeting)	1	1	Triage (Greeting)	0.10	0	27.0%
Triage (Nurses)	2	2	Triage (Nurses)	40.26	42	91.3%
Dispensing (Single)	2	2	Dispensing (Single)	0.07	0	54.7%
Dispensing (Multi)	2	2	Dispensing (Multi)	9.98	10	69.8%
Total service staff	9	9	Total	72.73		
Total staff	39		Total	0.00		

Values in red signify below-minimum staffing levels.

Values in red denote the "worst" station for that characteristic.

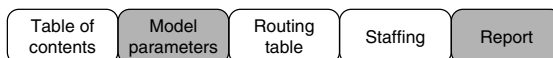


Figure 5: Using the capacity-planning and queueing model setup dialog and interface, planners can enter information specific to their applications and specify the staffing at each work station. The values in red in the screen shot are represented in bold in this figure.

Station	Number of staff	Station capacity (residents per hour)	Percentage of residents served	Constraint on clinic capacity (residents per hour)
Triage	2	463	100.0	463
Registration	9	4,444	97.3	4,567
Education	8	600	97.3	617
Screening	16	558	97.3	574
Consultation	7	111	25.5	437
Vaccination	16	294	95.8	307
Symptoms	1	49	4.8	1,037
Contact	1	16	3.2	498

Table 2: Each work station sets a constraint on clinic capacity based on its capacity and the percentage of residents that it serves. In this example, the clinic capacity is 307 residents per hour.

the clinic. Allow adequate space between work stations for residents waiting in line.

Clinic Operations

The guidelines for clinic operations include the following: Regulate resident arrivals carefully. Triage residents as early as possible in the process.

Work-Station Layout

The guidelines for laying out work stations and moving residents through a work station include the following: Use flow-through work station designs (Figure 6). Provide quiet rooms for education work stations where residents watch a video.

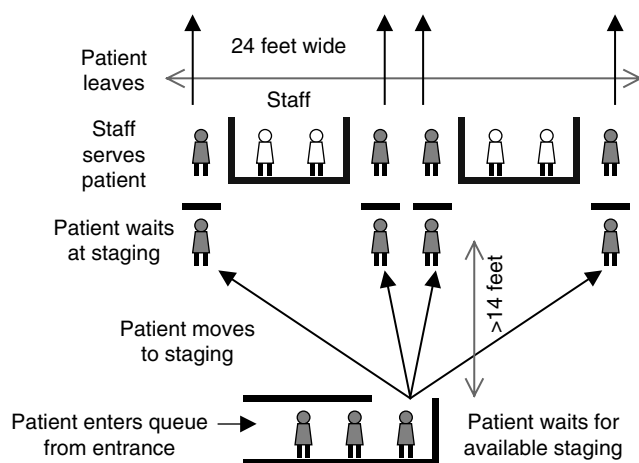


Figure 6: A flow-through layout for a clinic work station permits residents at the head of the queue to see when servers become available, stages the next residents to avoid wasted idle time for staff, and avoids interference caused by residents turning back after completing service.

Work-Station Operations

The guidelines covering operations at individual work stations include the following: Use multiple, small education classrooms instead of one large education classroom. Run education classes continuously. Provide residents with clipboards and pens so that they can fill in forms while waiting in line.

Conclusions

This work is the beginning of an exciting process of using operations research to improve planning for bioterrorism attacks, pandemic flu, or other events. Poorly conceived plans can cause confusion, delay responses to events, and reduce the effectiveness of responses, all of which increase the number of victims.

Our models and guidelines are helpful tools for creating good plans and improving existing ones. Planners can use the models to determine the number of staff members they need to achieve the capacity they need, and to design clinics that avoid unnecessary congestion. The models are based on data collected from clinic exercises, and they have been validated by those exercises and by public health professionals.

We are continuing to develop the models and guidelines based on feedback from the public health professionals using them. Because they are not, fortunately, operating mass-dispensing and vaccination clinics, further validation will come from exercises and from similar clinics set up to limit the spread of more common diseases (such as influenza).

Montgomery County, Maryland, is home to one of eight advanced practice centers (APCs) for public health preparedness. The APCs are building innovative programs and tools that prepare communities to respond to and recover from major acts of bioterrorism. CDC funds the APC program, which NACCHO administers. The APCs customize and package innovative tools for other local public health agencies to strengthen bioterrorism planning and response capabilities. NACCHO maintains an online clearinghouse of APC preparedness tools for local public health agencies (NACCHO 2005a). Our models will be available on this Web site for public health professionals to download and use. The long-term goal is to create and disseminate a broad set of methods and

guidelines to help county health departments create, assess, and improve their clinic plans.

While our guidelines include some suggestions on the details of workstation operations, further work is needed to study, improve, standardize, and document those details. Such improvements can increase the capacity of a work station (without adding staff) and reduce the variability of the task, which in turn reduces congestion in the clinic.

Mass-dispensing and vaccination clinics are an important part of larger responses that include staging areas, resident transportation, and medicine distribution. Those planning these parts of responses also need guidelines and models to form good plans.

Appendix. The Clinic Queueing Network Model

Analyzing queueing networks is a well-known problem, and analysts have developed different approximations for the general case. The following model is based on relationships that were independently derived, along with those provided by Hopp and Spearman (2001) and Buzacott and Shanthikumar (1993). We use i throughout to denote a station, with 0 referring to the bus arrival process, 1 through I referring to the stations in the clinic, and $I + 1$ referring to the exit.

Inputs

- P = size of population to be treated (residents).
- L = time allotted for treatment (days).
- h = daily hours of operation (hours per day).
- N = number of clinics.
- m_i = number of staff at station i .
- t_i = mean process time at station i (minutes).
- σ_i^2 = process time variance at station i (minutes²).
- k_i = processing batch size at station i .
- d_{ij} = distance from station i to station j (feet).
- v = average walking speed (feet per second).
- P_{ij} = routing probability from station i to station j .
- k_0 = bus arrival size.
- c_{a1}^2 = arrival SCV at station 1.

Calculated Quantities

- r_i = arrival rate at station i (residents per minute).
- c_{ai}^2 = arrival SCV at station i .
- c_{ei}^2 = processing time SCV at station i .
- c_{di}^2 = departure SCV at station i .

Outputs

- TH' = required throughput (residents per minute).
- m'_i = minimum staff at station i .
- CT_i = cycle time at station i (minutes).
- TCT = total average time in clinic (minutes).
- WIP = average number of residents in clinic.
- R = clinic capacity (residents per minute).
- w_i = average wait time at station i (minutes).
- W_i = average time spent traveling to the next station after station i (minutes).
- Q_i = average queue length at station i .
- u_i = utilization at station i .

The throughput required to treat the population in the given time is $TH' = P/60LhN$.

If residents arrive individually, the user specifies the arrival variability c_{a1}^2 . Else, the resident arrival variability is given as $c_{a1}^2 = k_0 - 1$.

All arriving residents go to the first station. We calculate the arrival rates for the other stations based on the routing probabilities,

$$r_i = \begin{cases} TH', & i = 1, \\ \sum_{j=1}^{i-1} r_j P_{ji}, & i > 1. \end{cases}$$

We use station arrival rates to determine the minimum staff at each station, $m'_i = (r_i \cdot t_i)/k_i$.

We then use user-selected staff levels m_i to calculate station utilization, $u_i = (r_i \cdot t_i)/(m_i \cdot k_i)$.

We calculate the variability of arrivals, processes, and departures from each station:

$$c_{ai}^2 = \sum_{j=1}^{i-1} ((c_{aj}^2 - 1) \cdot P_{ji} + 1) \cdot \frac{r_j \cdot P_{ji}}{r_i},$$

$$c_{ei}^2 = \frac{\sigma_i^2}{t_i^2},$$

$$c_{di}^2 = k_i - 1 + k_i \left(1 + (1 - u_i^2) \left(\frac{c_{ai}^2}{k_i} - 1 \right) + \frac{u_i^2}{\sqrt{m_i}} (c_{ei}^2 - 1) \right).$$

The average time spent waiting at station i depends upon the process batch size,

$$w_i = \frac{k_i - 1}{2r_i} + \frac{1}{2} \left(\frac{c_{ai}^2}{k_i} + c_{ei}^2 \right) \left(\frac{u_i \sqrt{2m_i + 2 - 1}}{m_i(1 - u_i)} \right) t_i.$$

The average time spent traveling to the next station after station i depends upon the routing probabilities and the average walking speed,

$$W_i = \frac{1}{60v} \sum_{j=i+1}^{I+1} P_{ij} d_{ij}.$$

The cycle time at station i is $CT_i = w_i + t_i + W_i$.

We weight the station cycle times by their arrival rates to calculate the total average time in clinic,

$$TCT = \frac{1}{r_1} \sum_{i=1}^I r_i CT_i.$$

Other statistics we calculate include clinic capacity, the average queue length at each station, and the average clinic WIP:

$$R = \min_{i=1, \dots, I} \left\{ \frac{m_i r_1}{t_i r_i} \right\},$$

$$Q_i = w_i r_i,$$

$$WIP = r_1 \cdot TCT.$$

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Gordon Aoyagi, Director, Homeland Security Department, 101 Orchard Ridge Drive, Suite 250, Gaithersburg, Maryland 20878, writes: "I am writing about the queueing study conducted for Montgomery County's Public Health Services by Jeffrey W. Herrmann, Department of Mechanical Engineering and Institute for Systems Research, University of Maryland, College Park, Maryland. This study and

the associated planning tools were done as preparation for a major bioterrorism event or other public health hazard where it would be necessary to give medication to many or all residents of the county.

“In such a situation, time would be of the essence; staff and available sites would be in short supply. Moving people through lines in the most efficient way would be crucial. Having enough staff at each station—but not more than needed—is important for using limited staff.

“This particular study assumed an outbreak of smallpox where all residents of the County would need to be vaccinated within a window of about seven to ten days.

“Dr. Herrmann and his students developed a model that estimated the amount of time spent by residents as they went through each stage of an exercise conducted by the County’s Public Health Emergency Preparedness Team. Simulating a real event, residents went from one station to the next—registration or intake, education, medical counseling, paperwork, and getting the shots.

“After the demonstration, the queue time at individual stations and the total time were analyzed, and adjustments were made to the plan. Another demonstration was run using information from this analysis, and queue times were greatly improved. In addition, it was seen that some stations were overstaffed while others were understaffed. Using staff most efficiently is vital, especially medically trained staff who cannot be augmented with minimally-trained volunteers.

“Montgomery County has about almost a million residents. Where staff is limited and there is a deadline by which medication must be administered in order to be effective, our county’s ability to serve our residents in a timely manner is extremely important. The clinic planning models have helped us create better plans that assign the correct number of staff to the proper locations.

“In addition to administering medicine in time, efficiency helps keep people calm. During a bioterrorism event or a large natural disaster, a high degree of anxiety and worry is to be expected. Waiting in line, perhaps with young children, exacerbates the anxiety and frustration. Having a smoothly running effort is itself calming because it sends a message that those in charge know what they are doing and are prepared.

“People waiting longer in line require a larger number of facilities and staff because each facility can hold only a given number of people at one time. If the number of staff or facilities cannot be expanded, this potentially means that some residents may not get their medication within the designated time frame. The challenge during these types of emergencies is to achieve maximum effective throughput through efficient use of staff and facilities. The work of Dr. Herrmann has helped us achieve this.

“This model has since been tested in other jurisdictions where different types of facilities were used. For its exercise, Montgomery County used a high school with classrooms for different stations. Other jurisdictions have used a large convention center (with stations placed in one enormous hall) or a gymnasium. The model helped initial planning to lay out the flow before the exercises in these other jurisdictions and was useful in analyzing glitches or seeing possible improvements should a real-life exercise be necessary.

“Overall, this outstanding work has provided our emergency preparedness planners with substantial results that have significantly increased our level of readiness. We will continue to use these models to help us plan for and respond to these types of events. The work of Dr. Herrmann and the models developed provide critical planning and assessment tools to Public Health Departments in evaluating their capabilities to meet their mandates during public health emergencies.”