

A Dynamic Model to Support Surge Capacity Planning in a Rural Hospital

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Abstract

A system dynamics model was developed to help hospitals assess their ability to handle surges of demand during various types of disasters. The model represents all major flows of patients through a hospital and indicates how specific responses to a surge may ameliorate bottlenecks and their potentially harmful effects on patients. The model was calibrated to represent a specific hospital in West Virginia and was tested under three quite different surge scenarios: a bus crash, a chemical plant leak, and a SARS outbreak. Under the difficult conditions of the SARS scenario, avoidable deaths of patients awaiting emergency care could be effectively reduced by adding reserve nursing staff not in the emergency department, as might be expected, but in the overloaded inpatient wards. The model can help hospital planners better anticipate how patient flows may be affected by disasters, and identify best practices for maximizing the hospital's surge capacity under such conditions.

Introduction

Despite the ever-present risk of natural and man-made disasters, the healthcare system has never been well-prepared for their potential consequences (Levitin and Siegelson, 1996; Ghilarducci et al., 2000). The recent events of 9/11 and the emergence of virile infectious diseases, such as Severe Acquired Respiratory Syndrome (SARS), emphasize the need for continued planning to ensure appropriate, sufficient, and timely healthcare system response (JCAHO, 2003).

Sufficient healthcare response includes the ability of a healthcare system to ramp up quickly to handle a large surge in patient load—an ability known as surge capacity. Although hospitals and public health agencies are modestly more prepared now than prior to 9/11 (GAO-03-373, 2003; Hoard et al., unpublished data; Becker et al., 2003), adequate planning for surge capacity is an area that has been generally overlooked (Heinrich, 2003; Franaszek, 2002).

Many hospitals, and in particular their emergency departments (EDs), already operate near or over capacity much of the time (JCAHO, 2003). ED overcrowding is caused by a number of inter-connected issues (Fatovich, 2002) and can compromise quality of care (Fatovich, 2002) and safety (Gore and Hughes, 2003).

The Center for Rural Emergency Medicine (CREM) decided to pursue System Dynamics modeling as a way to evaluate the dynamic complexities of disaster planning in healthcare. Although the issue of surge capacity can span the entire healthcare spectrum, the project team decided to focus initially on the surge capacity of a small rural hospital. Our broader research agenda is outlined in the paper, “Systems modeling in support of evidence-based disaster planning for rural areas” (Hoard et al., 2005).

Hospital Readiness

Hospitals of all sizes are now required to have disaster plans. Foremost in these plans is a hospital's ability to effectively address surge capacity. If they cannot do this within their own system, then they must take steps to shore it up, either with permanent or temporary (reserve) resources, or perhaps through flow-control methods such as triage, transfer, and early discharge.

A recent report by the General Accounting Office (GAO) suggests three indicators for identifying an overcrowding event: the number of hours that an ED is on ambulance diversion, the proportion of patients (so-called “walkouts”) who voluntarily leave the ED because of the delay in receiving a medical evaluation, and the proportion of patients and length of time that patients “board” in the ED. Ambulance diversion refers to the fact that when the ED is overcrowded, a hospital may decide to divert new ambulance arrivals to other hospitals (Fields, 2004). ED boarders are patients who have been completed ED care and are waiting to get admitted to a staffed inpatient bed. Increased ED boarding reflects an inability to move patients who were already screened and stabilized by emergency staff out of the ED and into inpatient beds (GAO-03-60, 2003; Asplin, 2003).

Many hospitals experience a combination of fluctuating and unpredictable demands of ED admissions and a persistently high inpatient census (Burt, 2004; Capwell, 1996; Crossen-White, 1998). Researchers have identified the need to study the ways in which a random surge of emergency admission may affect the utilization of ED and inpatient beds (Bagust et al., 1999). A previous system dynamics model examined the impact of hour-by-hour demand on an Accident and Emergency Department in the United Kingdom,

with particular emphasis on how waiting times for admission may lead to the postponement or cancellation of elective procedures (Lane et al., 2000).

Traditionally, EDs have provided a community benefit as the one place available to patients all hours of the day regardless of ability to pay, and they are critical for responding to emergencies of any size or type (e.g., public health, terrorism and natural disasters). Crowding limits the ability of EDs to fulfill their community benefit function in responding to such emergencies (Cunningham and May, 2003). However, in recent years, hospital administrators have had to respond to the financially-driven need for greater operational efficiency by reducing bed capacity and increasing occupancy rates. Consequently, even within the limits of normal day-to-day operations, hospitals and their EDs may be stretched to the limits by modest surges that test their ability to manage and streamline existing resources.

Rural America has its own particular challenges with healthcare delivery. Seventeen percent of the U.S. population lives in non-metropolitan areas (ERS, 2003), and hospitals in rural communities serve as a logical focal point for community reaction to a bioterrorist event (Schur, 2004) or any multiple casualty incident that tests the hospital's capacity to handle a surge in patients. Most of these rural areas have limited resources and capacity (Moscovice, 2004; ORHP, 2002), a relatively small number of providers (AHA 2003), and volunteer rather than professional Emergency Medical Services personnel (ORHP, 2002). Also, the geographic isolation of rural areas can greatly extend the time required for external help to arrive in extreme situations, particularly when exacerbated by poor road conditions and weather. These limitations of rural areas detract from their surge capacity and complicate response planning (CRHP, 2004).

In dealing with difficult medical cases, rural hospital EDs typically stabilize and then transfer patients to larger facilities that can provide higher levels of care (Williams et al., 2001). But the "safety valve" of transfers may not be available when a disaster causes the rural hospital to become isolated, or when the disaster is so widespread (as in an infectious disease epidemic) that even the large hospitals are operating at full capacity and cannot accept transfers.

System Dynamics Approach

Why have we taken a System Dynamics (SD) approach to studying rural hospital surge capacity planning? Given the many variables that may affect a hospital's ability to handle even a minor surge in patient flow and that distinguish one type of surge from another, it is impossible to assess surge capacity using one simple formula involving numbers of staff, beds, and equipment. It is also not possible to use historical data on a hospital's operations to assess its surge capacity. First, historical data are inadequate to cover all possible surge scenarios. Second, hospital resources and their configuration frequently change over time, so that a look backward at surge response may not accurately indicate how well the hospital would perform today under similar circumstances. Third, if we not only want to measure surge capacity, but also test ways of improving it, the historical method obviously will not work.

SD simulation has been used by other researchers to analyze patient flows in hospitals and other health care facilities (Homer and Hirsch, 2005). It is well-suited for testing alternative implementation strategies in the dynamically complex and constantly shifting

settings that characterize health care, and for considering many possible conditions and scenarios imposed upon such settings (Sterman, 2000; Homer et al., 2004).

In contrast with other formal methodologies, SD modeling allows one to consider self-correcting and self-reinforcing feedback loops that may become important in a surge situation, and to do so in a model that can be easily and thoroughly tested and understood. Self-correcting feedback loops, which help to mitigate the impact of a surge, appear wherever there are reserve resources, staff and beds that can be called upon when the need arises. Self-reinforcing feedback loops, on the other hand, can exacerbate the impact of a surge. One such loop involves the clinical deterioration of patients awaiting admission to the ED: The more that such patients deteriorate, the more load that represents on the ED, thereby extending further the waiting times for other patients and allowing their further deterioration.

Methods

This project was completed in three stages by a modeling team made up of researchers from West Virginia University (WVU) Center for Rural Emergency Medicine (CREM)—with expertise in emergency medicine, hospital systems, and public health—and an expert SD practitioner.

In *Stage 1* we constructed an initial “straw-man” proof-of-concept model based on in-house expertise and literature review. We also considered the various sorts of surge scenarios that a model should be able to evaluate. Through testing the straw-man model, we gained an initial appreciation of what might be the important assumptions and constraints differentiating one hospital from another in terms of its surge capacity, and the key parameters that could differentiate one surge scenario from another.

Stage 2 involved further development of the model and its application to an actual hospital in rural West Virginia. St. Joseph’s Hospital (SJH) was selected for its location and size, and because hospital management was enthusiastic about the aims and approach of the project and understood that modeling might help them to do a better job of disaster planning. Several employees of SJH participated, including the managing physician of the ED, nurse managers and schedulers, and hospital administrators. Three day-long sessions at SJH (1) introduced these participants to the straw-man model and the SD approach, (2) allowed us to revise the contents of the model to better fit their circumstances, and (3) allowed us to ensure that the scenarios and policy options being tested were realistic in their assumptions and results.

During Stage 2, “baseline” conditions were defined, based in part on recent SJH patient log data over a two-month period during which no unusual surges occurred. The baseline conditions describe average patient flows (and initial census levels), as well as nurse staffing levels, by day-of-week and hour-of-day. Surge scenarios could then be defined in terms of incremental change to patient inflows relative to the baseline.

During *Stage 3* we identified and detailed three different plausible surge scenarios. The three cases—a bus crash, a chemical plant leak, and an outbreak of Severe Acute Respiratory Syndrome (SARS)—represent a range in terms of their magnitude, duration, and severity, and in terms of the types of patient care required. Outcomes from each of the three surge scenarios were compared with the baseline to identify their differential impacts, and potential strategies were tested to determine their ability to improve surge capacity and reduce the adverse consequences of surges.

An Institutional Review Board duly approved protocol for the study.

Results

Model Structure

Figure 1 shows, in simplified form, the model's depiction of patient flow through the hospital. For example, the figure simplifies by showing "Pts await/in surgery" and "Pts await/in elective non-surgery" as single boxes, whereas in the model, there are actually separate boxes for "await" and for "in." Boxes represent accumulations or stocks of patients. The arrows with valve symbols represent flows of patients. A cloud at the end of a flow represents a source or sink of patients that starts or ends outside the hospital. Flows into the hospital must be specified as time series inputs to the model. These inflows include arrivals of patients to the ED, the scheduling of elective surgeries and non-surgeries, and direct arrivals to inpatient wards. Flows out of the hospital include discharges from all locations (ED, elective surgery and non-surgery, wards), walkouts of patients awaiting ED admission, and transfers of patients to other hospitals from ED and wards.

The model contains about 1,500 parameters, of 5 types:

- Assumed constants and initial values of patient stocks (about 150)
- Assumed time series inputs (28)
- Assumed X-Y lookup functions (4)
- Calculated patient stocks (about 300)
- Calculated flows and flow rates, waiting times and other outcome variables, and situation-dependent decision variables (about 1,000)

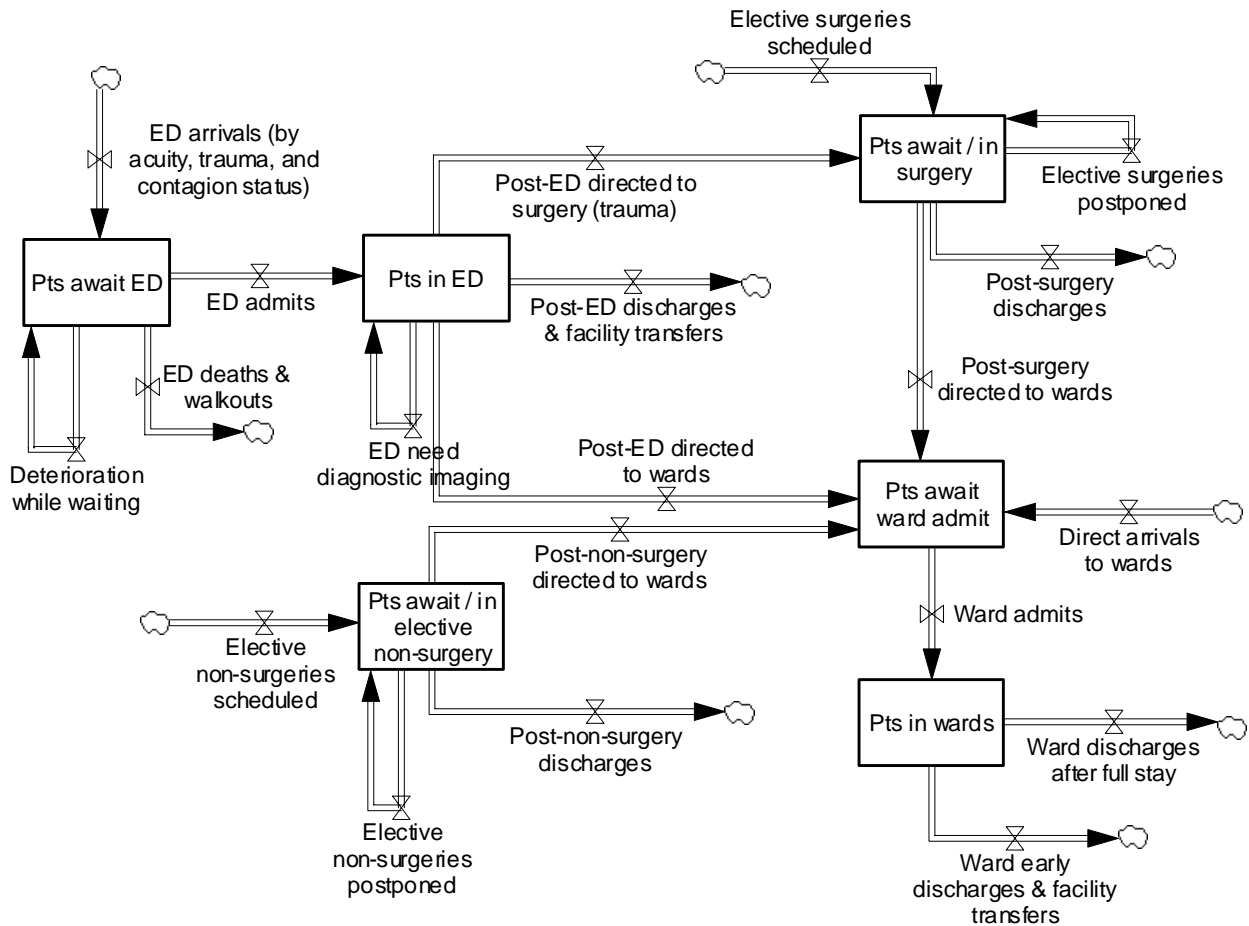
Patients are differentiated along four dimensions, some subsets of which apply depending on location within the hospital:

1. Triage type (for ED patients): Green, Yellow, Red, Black (dead) (Pedrotti and Perry, 1999);
2. Acuity type (for surgery and ward patients): Regular, High;
3. Presence of trauma (for ED patients): No, Yes;
4. Risk of contagion/need for isolation (for all locations): No, Yes.

The model steps through all equations at simulated 15 minute intervals, tracking day-of-week and time-of-day as it proceeds. Simulations described here are all 20 days, or 480 hours, in length, starting at 12 AM (midnight) on a Monday and ending at 12 AM on a Sunday.

Many of the model's equations help to specify the determination of patient flows. Among the most intricate equations are those dealing with admission to the ED and the inpatient wards. ED admission is modulated by the availability of constraining resources, which in the model include ED nurses and beds. If ED admission is constrained, then patients are prioritized based on their evaluated triage status, with Red a higher priority than Yellow, and Yellow higher than Green. However, this prioritization scheme may break down if there is a glut of patients awaiting ED admission, and ED nurses end up falling behind on required triage or hourly re-triage of patients.

Figure 1. Overview of model stock-and-flow structure



Similar to ED admission, inpatient ward admission is modulated by the availability of ward nurses and beds. If ward admission is constrained, then high acuity patients have higher priority for admission than regular acuity patients.

Resource constraints may also affect intake for surgery and elective non-surgical procedures. A lack of OR nurses or beds may limit intake into surgery and cause postponement of some elective procedures. If surgery is constrained, then emergency trauma surgeries have higher priority than elective ones, and elective surgeries may be postponed to the following day. In regard to elective non-surgical procedures, a lack of outpatient nurses may limit intake and cause postponement of some of these to the following day.

Another possible reason for postponement of elective surgeries or non-surgeries is if there is an extended delay for inpatient ward admission. A large fraction of surgical patients are directed to wards post-surgery, so postponement of surgery can help to alleviate the build-up of patients awaiting ward admission. Also, though only a very small fraction of non-surgical outpatients are directed to a ward post-surgery, such direction usually occurs because of an acute event during the outpatient procedure

requiring immediate ward admission, which could put the wards in a difficult situation if they are already at capacity.

The postponement of elective procedures due to ward admission delay is an example of a compensating feedback response, or “safety valve,” that can help to alleviate bottlenecks that may develop during a surge. The model includes other realistic feedback responses by the hospital and by patients. These include, (1) the cancellation of some diagnostic imaging for ED patients if there is a long wait for the same (due to insufficient technician capacity to meet the demand); (2) the early discharge of some ward patients if there is a long wait for ward admission; and (3) ED patient walkouts by the “walking wounded” (triage Greens and some Yellows) if there is a long wait for ED admission.

In addition to these compensating feedback loops, the model includes a self-reinforcing feedback loop in the ED: a potentially troublesome vicious cycle that is related to the possibility of patient deterioration while waiting for ED admission. If ED nurses become temporarily overloaded leading to extended ED waiting times, some Greens may deteriorate to Yellow, and some Yellows to Red, as they await admission. In addition, a small fraction of Reds may deteriorate to Black, indicating an avoidable death. Although death from deterioration actually alleviates demand on the ED, it is the ultimate indicator of inadequate surge capacity. Patients with more severe conditions require a higher nurse-to-patient ratio than those with less severe conditions, so the deterioration of patients place an even greater load on the ED, extending waiting times, therefore leading to the possibility of further patient deterioration.

The model was calibrated to represent SJH, in terms of its nursing and bed resources, its typical patient inflows, and the way it responds to overload conditions. This calibration and associated assumptions are described in Appendix Tables 3a, 3b, and 3c.

The baseline “no surge” scenario for ED arrivals assumes—for the sake of easy comparison—a consistent volume, unchanged from day-to-day or week-to-week; Table 3a (item 1.1), Table 3b (3.1, 4.1), and Table 3c (5.1). Given all other assumptions in the model, simulation indicates that this volume is well handled by the hospital and results in no significant patient bottlenecks, and only a small amount of waiting in the ED during the peak afternoon hours of each day. The project team at SJH inspected the model’s response to the baseline demand scenario, and declared that it presents a faithful picture of the hospital’s typical patient flow and load situation.

Scenario Testing

Description of surge scenarios: Note these volumes are in addition to the normal 50-per day ED volume of the no-surge baseline.

Bus crash: 45 patients arrive ED Day 3 (Wednesday) 6-8 PM; plus 15 dead on the scene (impact of dead patients would effect utilization of available EMS resources).

Arrival distribution: 25 G, 9 Y, 6 R, 5 B; 100% with trauma injury (no contagion).

Chemical plant leak: 100 patients arrive ED Day 1 (Monday) 2-7 PM; plus 25 dead on the scene. Arrival distribution: 45 G, 30 Y, 25 R, 0 B; 5% with trauma injury (no contagion).

SARS outbreak: 837 pts arrive ED Days 2-14, according to Singapore model (CDC, 2004), with peak of 106 on Day 10. Distribution: 377 G, 333 Y, 106 R, 21 B; 100% contagious (no trauma).

Key metrics for 20-day simulations are presented in Table 1. The bus crash and the chemical leak are short-lived events, causing only temporary difficulty, while SARS leads to more severe problems. Probably most significant indicator of difficulty are deaths while awaiting ED admit (avoidable deaths): 0 for the baseline and bus crash, 3 for the chemical leak, and 109 for the SARS scenario. This is related to the number of patient-hours awaiting ED admission, which indicates an ED admission bottleneck. Patient hours awaiting surgery and elective non-surgery indicate the postponement of procedures due to ward admission bottleneck.

Note that although all 45 bus crash victims have trauma injury, only 6 surgeries are required (3 Yellows and 3 Reds). Because they arrive late in the day, when only the OR call team is available, only one surgery is done at a time. When the regular team arrives the following morning, the remaining surgeries are done immediately.

Whereas the bus crash puts stress primarily on the ED, the chemical leak disaster puts stress on both the ED and on the wards. The reason is not so much the difference in total ED arrivals (100 vs. 45) as it is the difference in more severe arrivals: the Reds (25 vs. 6) and the Yellows (30 vs. 9). It is only the more severe arrivals who are directed to wards: 30% of Yellows, and 50% of the Reds. The other 50% of Reds are transferred to other hospitals for specialized treatment. Long waits for ED admission (up to 13 hours) in the chemical leak case start on Day 1 and are eliminated by Day 2, thanks in part to walkouts by many Greens and some Yellows. Long waits for ward admission (up to 12 hours for regular acuity patients) start on Day 3 and extend to Day 4, leading to some elective procedure postponements and early ward discharges.

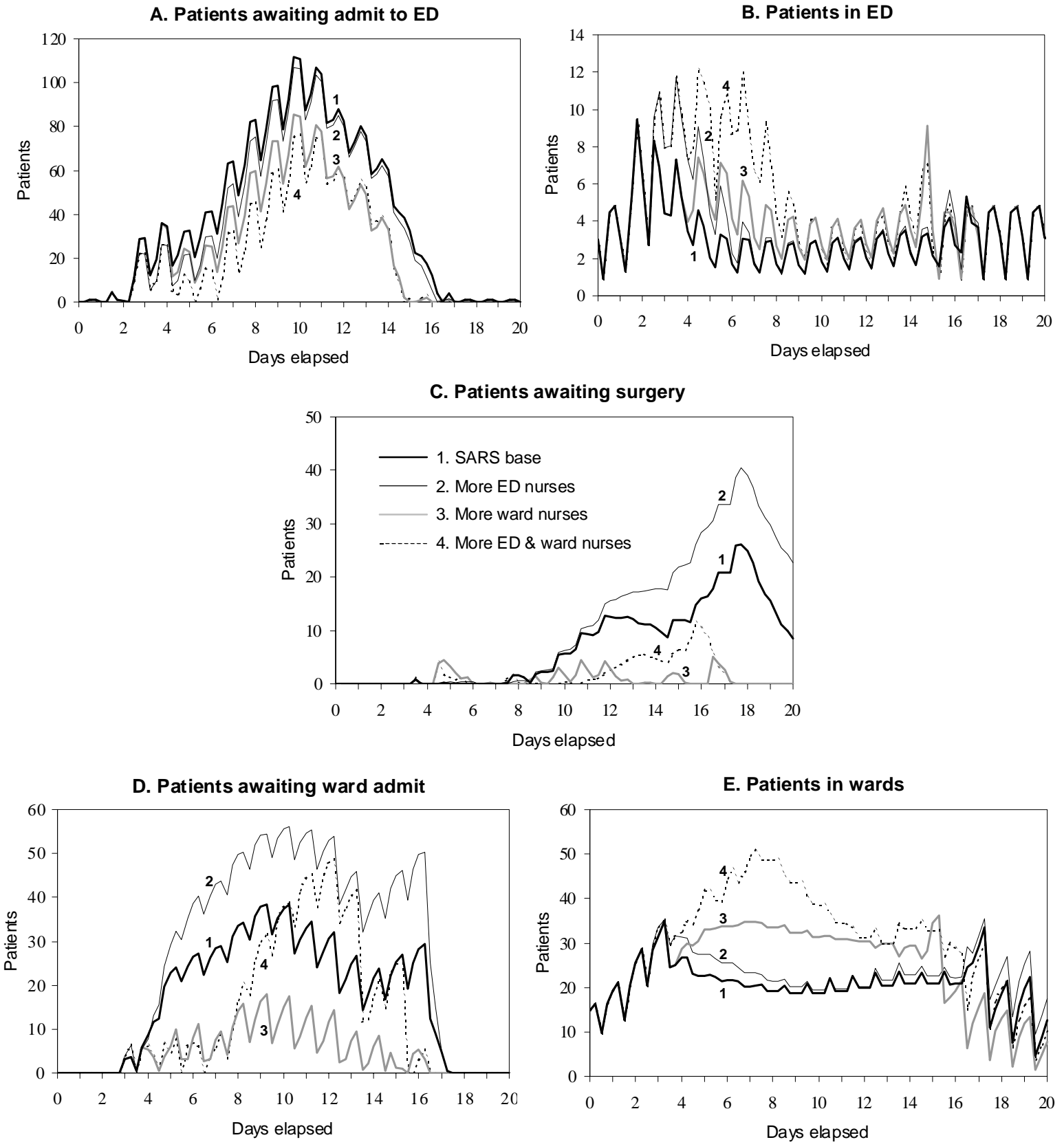
Similar to the chemical leak disaster, the SARS outbreak creates difficulties for both the ED and the wards, but does so for many more days and with much more severe consequences in terms of the number of avoidable deaths, patient hours spent waiting for admission, early ward discharges, and postponement of elective procedures. Some of these dynamics are reflected in Figure 2, which contains graphs for key patient stocks in ED, surgery, and inpatient wards; in each graph, see the thick black line labeled “1. SARS base.”

In the SARS scenario, ED waiting times start to increase on Day 3, and keep elevating steadily until they reach 40 to 50 hours by Day 13, remaining at that level for 4 days until they finally return to zero during Day 17 (three days after the end of the outbreak). This huge bottleneck persists despite the fact that more than half of the ED arrivals over the 20 day period of simulation walk out. Also, in a seeming paradox, significantly fewer patients are admitted into ED care in the SARS scenario than in any of the other three scenarios, despite the greater level of demand (see Table 1). One reason for the reduced ED intake in the SARS scenario is that the SARS patients absorb 25% more nursing time and spend an average of 50% more time in the ED by virtue of their being in isolation. However, the more important reason for reduced ED admissions, is that the wards reach capacity (in terms of what the nursing staff can handle), and consequently, ward admissions slow to a trickle. (Note that isolation of SARS-infected patients makes things more time-consuming in the wards as it does in the ED.) This ward bottleneck leads to growth in the number of patients “boarding” in ED awaiting ward admission, thereby absorbing a large amount of ED nursing time and detracting from the

Table 1. Surge scenario outcomes after 20 simulated days

	No Surge Baseline	Bus Crash	Chemical Leak	SARS
Max ED arrivals in a day	50	95	150	156
ED arrivals	1005	1050	1105	1842
Max pts awaiting ED admit	2	38	88	115
Patient hrs awaiting ED admit	226	430	1137	18712
Deaths while awaiting ED admit (Avoidable deaths)	0	0	3	109
ED walkouts	9	29	79	940
ED admits	991	1010	1018	767
DI studies skipped in ED	0	2	2	9
ED nurse hours utilized	1200	1230	1273	2079
Max pts awaiting surgery	0	4	11	29
Patient hrs awaiting surgery	0	54	309	3476
Max pts awaiting elective non-surgery	0	0	8	13
Patient hrs awaiting elective non-surgery	0	0	127	519
Max pts awaiting ward admit	0	0	8	39
Patient hrs awaiting ward admit	0	0	258	8340
Ward admits	279	289	302	344
Ward early discharges	0	0	11	43
Ward nurse hours utilized	2880	2880	3015	4231

Figure 2. SARS scenario patient stock dynamics under alternative reserve-staffing policies



time ED nurses can spend with new ED admits—and therefore limiting the number of such admits.

Note also that the postponement of elective surgeries becomes a problem in the SARS scenario; such postponement is triggered when ward admission delays have grown sufficiently, more than halfway through the outbreak period. These postponements begin on Day 8, and by Day 18, more than 25 patients are awaiting surgery, and then subsiding gradually, as the OR call team works off the backlog one surgery at a time. By the end of Day 20, there are still 8 patients awaiting postponed elective surgeries. Thus, some repercussions of the SARS outbreak are still felt nearly a week after the surge of ED arrivals has concluded.

Policy Testing

A variety of simulation experiments were performed, all designed to identify where the hospital's procedural policies should be modified, or its reserve resources bolstered, in order to make the hospital better to cope with demand surges. In looking for ways to improve hospital performance under surge conditions, we have taken the lead from the project team members at SJH Hospital, who indicated what types of changes might be feasible.

In regard to procedural policies, we have experimented with changes in the practices of diagnostic imaging (DI) cancellation, elective surgery postponement, elective non-surgery postponement, and early ward discharge. The model suggests that all of these policies, with the possible exception of non-surgery postponement, can be helpful in managing surges. Because only one percent or so of elective non-surgeries end up impacting the wards (which is rather insignificant, even taking into account the fact that the cases directed to wards are typically ones of high acuity), it is not clear that there is enough benefit from postponing such procedures to justify the disadvantages of doing so.

In regard to reserve resources, the SJH team indicated the possibility of some increases in reserve nursing staff, specifically in the ED and inpatient ward areas, and also allowing for a reserve DI technician. Such reserve staff could be drawn from off-duty or part-time hospital staff, from office-based nurses and technicians in the community, or from retired nurses and technicians in the community.

- *ED reserve nurses:* The baseline model assumes that in addition to the normal complement of 3 day-shift staff and 2 night-shift staff, another 3 day nurses and 2 night nurses are available as needed during a surge. The project team felt that the reserves could be increased to 5 day and 4 night, to give a maximum total of 8 day (=3 regular + 5 reserve) and 6 night (=2 regular + 4 reserve) nurses in the ED during a surge.
- *Ward reserve nurses:* The baseline model assumes that in addition to the normal complement of 6 ward nurses (all hours), 4 reserves nurses (all hours as well) are available as needed during a surge. The project team felt that the reserves could perhaps be increased to 8, to give a maximum total of 14 (=6 regular + 8 reserve) nurses in the wards during a surge.

- *DI reserve technician:* The baseline model assumes one technician or technician-equivalent (FTE) is available at all hours specifically for ED and ward patient imaging needs. Other DI technicians may be present to work on diagnostic imaging associated with elective procedures. The project team felt that one reserve DI technician position (all hours) could perhaps be created, to give a maximum total of two (=1 regular + 1 reserve) DI technicians during a surge.

We have experimented with increases in reserve staff in conjunction with the bus crash, chemical leak, and SARS surge scenarios. Because the benefits of such increases are more obvious when the scenario creates more difficulty for the hospital, we will focus here on the impacts of reserve staff on SARS scenario outcomes. Table 2 presents the key outcome metrics from five 20-day simulations, as follows:

1. SARS base: Uses baseline assumptions for reserve staff (same simulation as in the last column of Table 1).
2. More ED nurses: Increases the ED reserve nurse contingent as described above.
3. More ward nurses: Increases the ward reserve nurse contingent as described above.
4. More ED and ward nurses: Increases both reserve nurse contingents as described above.
5. More nurses and DI techs: Increases both reserve nurse contingents and creates a reserve DI technician position as described above.

Figure 2 shows graphically how the first four of these simulations differ, over time, in terms of the accumulation of patients at different points in the hospital. The fifth simulation is similar to the fourth in its dynamics, and has been left out of Figure 2 for the sake of legibility.

It is evident from Table 2 and Figure 2 that by adding more reserve ward nurses, it is more effective than adding more reserve ED nurses in reducing bottlenecks and improving hospital performance under the SARS scenario. The boosting of ward nurses dramatically reduces the number of patients awaiting admission, not only to the wards themselves (Figure 2d), but also to surgery (Figure 2c) and to the ED (Figure 2a), reducing the number of avoidable ED deaths from 109 to 52. By contrast, the boosting of ED nurses is ultimately much less effective, reducing avoidable ED deaths only to 94, and actually causing a large *increase* in the numbers of patients awaiting surgery and ward admission.

Close inspection of the graphs reveals that boosting ED nurses is initially *more* effective at reducing the ED backlog (Figure 2a) than is boosting ward nurses, but only for the first four days of the outbreak (through Day Five). After Day 4, the addition of ED nurses becomes increasingly ineffective at reducing the ED backlog, resulting in virtually no improvement over the baseline SARS run from Day 10 through Day 16. This sort of diminishing policy impact over time has been described as *policy resistance* (Sterman 2000). The source of the policy resistance in this case is the greater build-up of patients awaiting ward admission when the number of ED nurses is increased but the number of ward nurses is not. Nearly all of these waiting patients are post-ED boarders and are still the responsibility of the ED nurses. The net effect of this backlash effect is to neutralize the benefit of adding more ED nurses in terms of their capacity to care for

new ED admissions. By Day Eight, the capacity of the ED to care for new patients (Figure 2b) is no greater with additional ED nurses than it was under the baseline policy.

The story is quite different with the boosting of ward nurses. By raising the capacity of the wards to care for patients (Figure 2e), the ward backlog is cut substantially, and results in a much reduced load of boarders for the ED. Consequently, although there is no increase in the number of ED nurses, the capacity of the ED to care for new patients (Figure 2b) is increased. This improvement starts the third day of the SARS outbreak (Day 4) and continues until one day after the end of the outbreak (Day 15). With the additional ward nurses, the ED backlog is eliminated two days earlier than in either the baseline SARS run or in the run with more ED nurses only.

Next consider what happens when the numbers of ED nurses and ward nurses are both boosted. The result is smooth performance of the entire hospital for the first 6 days of the outbreak (Days 2 through 7), with both ED and ward backlogs staying low (Figures 2a, 2d), and the patient throughput of both ED and wards remaining high (Figures 2b, 2e). As the number of new SARS arrivals to the ED continues to grow—peaking on Day 10 before it starts to subside—ward nursing capacity becomes strained. Recall again that isolated SARS patients are significantly more time-consuming than non-isolated patients. Although the number of ward beds may be sufficient to accommodate a large number of such patients, the greater time requirements may cause even an increased number of nurses to become overloaded. Consequently, the ward backlog climbs quickly through Day 12. This, in turn, leads to a situation in which the ED backlog is no better off from Day 11 onward with additional ED and ward nurses than it is with additional ward nurses alone. Nonetheless, the combination of additional ED and ward nurses still results in fewer avoidable ED deaths than with additional ward nurses alone (41 vs. 52).

Consider finally what happens when an additional DI technician supplements the addition of ED and ward nurses. The most obvious benefit is that the number of deferred DI studies is cut dramatically, from 89 to 26 (Table 2). Note that the simulation with more ED and ward nurses is the only one in which the number of DI studies not completed is relatively large. This greater skipping of DI studies indicates that DI has become backlogged. With the downstream bottleneck of ward admission and the upstream bottleneck of ED admission both largely removed by adding nurses, diagnostic imaging becomes the new location where a backlog may develop. The DI bottleneck is less damaging than either of the other two, however, because the option of skipping DI keeps patients flowing through the ED rather than getting stopped up there. However, the skipping of DI does increase the fraction of Yellows directed to wards (from 30% to 60%), and places a greater burden on the wards. That is why, when a second DI tech is added, the number of ward admits, as well as the number of patient hours awaiting ward admits, is reduced. The reduction of ward admits backlog in turn permits less of a build-up of patients awaiting ED admission, and so allows for a further reduction in avoidable deaths (from 41 to 35) when a second DI tech is added on top of the additional ED and ward nurses.

Table 2. SARS scenario outcomes under alternative reserve-staffing policies

	SARS base	More ED nurses	More Ward nurses	More ED & Ward nurses	More nurses & DI techs
Max pts awaiting ED admit	115	110	89	79	74
Patient hrs awaiting ED admit	18712	16622	12271	10146	8942
Deaths while awaiting ED admit (Avoidable deaths)	109	94	52	41	35
ED walkouts	940	856	809	686	604
ED admits	767	866	955	1088	1176
DI studies skipped in ED	9	35	21	89	26
DI tech hours utilized	480	480	480	480	568
ED nurse hours utilized	2079	2752	1985	2568	2502
Max pts awaiting surgery	29	42	6	12	12
Patient hrs awaiting surgery	3476	5582	400	823	771
Max pts awaiting elective non-surgery	13	14	7	7	7
Patient hrs awaiting elective non-surgery	519	531	243	176	176
Max pts awaiting ward admit	39	56	19	49	49
Patient hrs awaiting ward admit	8340	13344	2413	6370	6230
Ward admits	344	359	395	430	425
Ward early discharges	43	59	46	65	65
Ward nurse hours utilized	4231	4225	5124	5084	4916

Discussion

Hospitals have an essential role to play in community preparedness for emergencies of all sizes. The ED in a hospital is often considered the safety net for health care, accepting all comers in all conditions. Many believe that it is time for the hospital community to develop new strategies to support this safety net before it collapses (Adams and Biros, 2001; Richards and Hwang, 2001). Even a relatively small influenza outbreak can overwhelm the resources of many rural hospitals. Hospitals should develop standardized responses for both these smaller, more commonly experienced surges as well as for the less likely but more consequential mass casualty incidents (MCIs) that may also occur.

Published emergency preparedness scenarios have often been oriented to urban or densely populated areas. Although 20% of the nation lives in rural areas (Quality Through Collaboration, 2004), little action has been taken to understand the dynamics of rural preparedness, emergency care, and public health response specifically (Williams et al., 2001; Treat et al., 2001). This study was developed to better understand the requirements of surge capacity preparedness for a small rural hospital.

Using the SD approach, we have developed a modeling tool that could assist rural hospital and emergency planners in preparing for surge events that take place regularly (e.g., influenza), as well as those that have much less chance of occurring (e.g., bioterrorism).

The results of the SARS scenario policy testing seem to suggest that the first, best place for St. Joseph's Hospital to consider additional reserve nurses is in the inpatient wards. Only after doing so does it make sense for them also to expand the number of reserve nurses in the ED, and perhaps provide for reserve diagnostic imaging technicians.

Can these results be generalized to other surge scenarios and other hospitals? With a few conditional statements, we believe the answer is yes. The most important aspect of the SARS scenario that may differentiate it from other scenarios is that a large proportion of the patients are of sufficient acuity to require inpatient care. The need for isolation is another salient feature of the SARS scenario, but one that, along with the overall number of ED arrivals and the duration of the surge, has implications for the proper scaling of the hospital *overall* to deal with peak-load conditions, rather than for how the reserve resources in the hospital are *balanced* between ED and the wards and other locations.

Moving from the nature of the surge to the hospital itself, a couple of salient points about SJH need to be considered. The first point is that, for historical reasons, SJH has plenty of reserve bed capacity. Consequently, beds were not a limiting constraint in our SJH simulations, but might become constraining in other hospitals. A second point about SJH is that they regularly transfer a large fraction of their highest-acuity and most difficult ED and ward patients to other hospitals. In all of the scenarios tested, we assumed that this ability to transfer—a significant safety valve for SJH and other rural hospitals—was not interrupted. However, it should be recognized that most large, urban hospitals do not have such an ability to transfer patients, and that under certain disaster conditions smaller rural hospitals may lose much of that ability.

Conclusion

The focus of this study was on the internal processes of a small rural hospital and the determination of what specific locations in the hospital should receive higher priority for reserve capacity than others. The SD model that was developed is general enough to help hospitals of any size to plan and allocate resources more effectively and rapidly, and possibly mitigate loss of life and prevent further spread of infection or disease. We realize, however, that disasters can impact more parts of a healthcare system than only its hospitals. Hirsch (2004) and other researchers have recently begun to apply SD to investigate the implications of disasters for entire healthcare systems. We, too, would like to extend our work on surge response in this direction, tying in the roles of emergency medical services, as well as that of office-based physicians. We have previously described a research agenda for studying disaster response that starts with the hospital and works outward to encompass an entire community (Hoard et al., 2005).

As hospitals and other health planners struggle with plan development in regard to surge capacity, SD models can provide a more realistic view of what is likely to work and what is not, and under what circumstances. Simulations can provide useful information to hospitals in readying themselves to confront not only catastrophic mass casualty incidents, but also the more frequent surges that can overwhelm a small rural ED.

SD could provide healthcare professionals and policymakers the tools to better plan for surge capacity needed for public health emergencies of any size and could assist in developing best practices for rural healthcare preparedness.

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APPENDIX: BASELINE MODEL ASSUMPTIONS

Table 3a. Baseline model assumptions—Emergency Department and Diagnostic Imaging

1. Emergency Department (ED)

- 1.1. ED arrivals per day: 26 Green, 22 Yellow, 2 Red, 0.25 Black (die before admission); 40% with trauma (potentially requiring surgery), 3% contagious (requiring isolation).
- 1.2. ED arrivals go through daily cycle with minimum at 5 AM to 7 AM, building up to maximum at 11 AM to noon, then falling off gradually through afternoon and night. Minimum is 7% of maximum.
- 1.3. Normally 3 ED nurses work day shift (incl. 1 reserved for triage), 2 night shift; may increase to as many as 6 day and 4 night during a surge.
- 1.4. Normally 5 ED beds available; may increase to as many as 15 during a surge.
- 1.5. Triage capacity of 15 patients per triage nurse per hour.
- 1.6. Red has highest priority for ED admission, then Yellow, then Green. Re-triage required after each hour of waiting. If ED nurses insufficient to do all required triage and re-triage, then to that extent ability to prioritize patients is compromised.
- 1.7. Deterioration per hour of waiting: 10% of Greens deteriorate to Yellow, 5% of Yellows to Red; 1% of Reds to Black (death).
- 1.8. In the event of an ED bottleneck, some Greens walk out: 10% per hour if the wait is 2 hrs., 25% if 4 hrs., 60% if 8 hrs., 92% if 12 hrs, 100% if 16 hrs. or more. Yellow walkout rate is 20% of Green. No Red walkouts.
- 1.9. Average time to complete ED care, aside from diagnostic imaging, if not isolated: Green 1 hr, Yellow 1.5 hrs, Red 2 hrs. Isolation increases time by 50%.
- 1.10. Required nurse-to-patient ratio in ED if not isolated: Green 0.25, Yellow 0.5, Red 1. Isolation increases ratio by 25%.
- 1.11. 50% of Reds transferred out to other hospitals following ED evaluation (0.5 hour).
- 1.12. 30% of Yellows normally directed to wards (starting with surgery, if trauma) after ED care; 100% of Reds. But if a bottleneck in diagnostic imaging (DI) causes some Yellows to skip needed DI while in the ED (see 2.4 below), then 60% are directed to wards for testing and observation.
- 1.13. Required nurse-to-patient ratio for post-ED patients awaiting surgery or ward admission: Yellow 0.125, Red 0.25.

2. Diagnostic Imaging (DI)

- 2.1. 1 DI technician-equivalent is available at all hours for ED and ward patient imaging needs, and can do up to 2 cases per hour. Ward cases have priority over ED cases.
- 2.2. Fraction of ED patients needing DI: Reds 100%; Yellows 60-80% if not contagious, 100% if contagious; Greens 5-15% if not contagious, 85-95% if contagious.
- 2.3. Fraction of ward patients needing DI: 60% of regular acuity within 36 hours of admission; 80% of high acuity within 24 hours of admission.
- 2.4. In the event of a DI bottleneck, some needed DI for ED cases is skipped: 20% if the wait is 1 hr., 43% if 2 hrs., 70% if 4 hrs., 92% if 8 hrs., 100% if 12 hrs. or more.

Table 3b. Baseline model assumptions—Surgery and Elective Non-Surgery

3. Surgery/Operating Rooms (OR)

- 3.1. Elective surgeries scheduled: 8 per weekday, 0.5 per weekend day; scheduled to arrive at uniform rate 7 AM to 2 PM.
- 3.2. In the event of a bottleneck at ward admission, some elective surgeries are rescheduled to the next day: 40% if the waiting time for a regular-acuity admission is 2 hrs., 90% if 4 hrs., 100% if 6 hrs or more.
- 3.3. Average time to complete OR procedure: 2.0 hours elective, 2.75 hours emergency (trauma)
- 3.4. 15 OR nurses work weekdays 7 AM to 4:30 PM; 5 OR call team nurses available all other hours and all day Saturday and Sunday.
- 3.5. 3 OR beds available at all times.
- 3.6. Required OR nurse-to-patient ratio during surgery: 5.0 if not isolated; Isolation increases ratio by 25%.
- 3.7. Required OR nurse-to-patient ratio for post-surgery (boarding) patients: 0.25 regular acuity, 0.5 high acuity; Isolation increases ratios by 25%.
- 3.8. 75% of elective surgery patients directed to wards post-surgery, of whom 75% are regular acuity and 25% high acuity. 100% of emergency surgery patients directed to wards post-surgery; acuity indicated by triage color (Yellow: regular, Red: high).

4. Elective Non-Surgical Outpatient Procedures

- 4.1. Elective non-surgeries scheduled: 8.4 per weekday, 0.8 per Saturday, none on Sunday; scheduled to arrive at uniform rate 7 AM to 2 PM.
- 4.2. In the event of a bottleneck for ward admission, some elective non-surgeries are rescheduled to the next day: 40% if the waiting time for a regular-acuity admission is 2 hrs., 90% if 4 hrs., 100% if 6 hrs or more.
- 4.3. Average time to complete non-surgical procedure: 1 hr.
- 4.4. 3 outpatient procedure nurses work weekdays 7 AM to 4:30 PM; 1 outpatient nurse on call at all other hours and all day Saturday. (Outpatient beds not a limiting factor.)
- 4.5. Required nurse-to-patient ratio during outpatient procedure: 1.5.
- 4.6. Required outpatient nurse-to-patient ratio for post-procedure (boarding) patients: 0.25 regular acuity, 0.5 high acuity.
- 4.7. Only 1% of non-surgical outpatients directed to wards post-procedure, of whom 10% are regular acuity and 90% high acuity.

Table 3c. Baseline model assumptions—Inpatient Wards

5. Inpatient Wards

- 5.1. Direct ward arrivals: 1.4 per day including weekends. They go through a daily cycle with minimum at 5 PM through 6 AM, building up to maximum at 11 AM to 1 PM, then falling off gradually through afternoon. Minimum is 50% of maximum.
- 5.2. Usual length of stay in ward if not isolated: regular acuity 79 hrs., high acuity 99 hrs. If isolated: regular acuity 108 hrs., high acuity 128 hrs. Normal ward discharges occur 8 AM to noon.
- 5.3. In the event of a bottleneck for ward admission, some regular-acuity, non-isolated ward patients are discharged early: 5% per hour if the waiting time for a regular-acuity admission is 1 hr., 40% if 2 hrs., 70% if 3 hrs., 90% if 4 hrs, 100% if 6 hrs. or more.
- 5.4. Normally 6 ward nurses are available at all hours; may increase to as many as 10 during a surge.
- 5.5. Normally 28 ward beds available; may increase to as many as 47 during a surge.
- 5.6. Required nurse-to-patient ratio in wards if not isolated: Regular acuity 0.1, high acuity 0.5. Isolation increases ratio by 25%.
- 5.7. High acuity has higher priority for ward admission than regular acuity.
- 5.8. 30% of high acuity patients transferred out to other hospitals following initial 24 hours of testing and observation.