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EFFECT OF COUPLING BETWEEN EMERGENCY DEPARTMENT AND INPATIENT UNIT ON THE OVERCROWDING IN EMERGENCY DEPARTMENT

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ABSTRACT

Emergency Department (ED) overcrowding has become a common problem in the United States as well as other developed nations, threatening the safety of patients who rely on timely emergency treatment. Volume of high-acuity patients and the volume of patients that are later admitted to the inpatient unit (IU) are factors reported as major causes of ED overcrowding. These two factors can be interpreted to represent the strength of the interaction between an ED and its associated IU. In addition to confirming the observations reported in previous studies, we were able to use discrete event simulation to characterize the relationship between IU utilization and ED crowding: it was found that the sensitivity of ED overcrowding with respect to IU utilization depends on the degree of coupling between the two units. Our findings have potential implications in guiding a hospital's effort to optimize their system.

1 INTODUCTION

1.1 Background

Acute illness and traumatic injury happen around the clock. However, a lack of immediate availability of primary care systems or a lack of proper capabilities in such systems often makes an ED the only source for emergency medical care. As a consequence EDs have to provide timely emergency medical care as the around-the-clock gate to hospitals. In addition to providing emergency medical care, EDs in the United States have also become a source for providing safety net care to vulnerable populations who suffer from access barriers to primary care systems. With these roles in our healthcare system, the demand for ED medical care has been increasing, and, in 2002, more than 110 million ED visits were documented, which is a 23% increase compared to 1992 (McCaig 2004).

The increase in ED usage has been accompanied by an increase in ED overcrowding, which has already been a common, serious problem in the United States since 1990s (Andrulis et al. 1991; Derlet, Richards, and Kravitz 2000). According to a 2001 report, 91% of 575 US ED directors reported overcrowding, 39% on a daily basis (Cowan and Trzeciak 2005). This tendency has not changed, and we see the problem persists in today's EDs. For instance, as of today, an Emergency Room (ER) stay in Massachusetts reaches up to 8 hours as a result of ED overcrowding (Kowalczyk 2007).

A common perception of overcrowding is a situation in which there are more patients than staffed treatment beds and waiting times exceed reasonable levels. Typically crowding involves patients waiting for ED admission, admitted patients being monitored in non-treatment areas, and patients boarded in the ED awaiting transfer to the IU. When overwhelmed by overcrowding, EDs often attempt to relieve this demand-supply imbalance by diverting incoming ambulances. This is known as entering ambulance diversion status. While diversion status is intended to ensure critically-ill patients get timely medical care – by diverting them away from a facility where long wait is expected –, this can lead to a quite contrary, serious negative consequence if other nearby EDs happen to be in similarly crowded conditions: the diverted ambulances may be forced to take long detours, significantly delaying medical care. Indeed, some studies report higher trauma mortality rates for diverted patients (Asplin 2003; Brewer 2002).

The apparent imbalance in the supply and demand in an overcrowded ED is a result of various factors that can be grouped into three components, two of which are outside ED. The patient influx could be too high, the ED's capacity could be too small or the ED lacks necessary efficiency, or the patient outflux from ED is too low (Asplin et al. 2003). Among the numerous factors affecting ED overcrowding, it has been reported that major causes of ED overcrowding are "an increasing volume of high-acuity patients presenting to the ED and insufficient inpatient capacity" (Cowan and Trzeciak 2005; CAEP 2001; CAEP 2007; ENA 2005; Issue Brief 2001; Olshaker and Rathley 2006; Rathlev et al. 2007; Schull et al. 2003; US GAO 2003). Schull, Kiss, and Szalai (2007) tested the controversial question of the extent to which patients with minor conditions contribute to delays and crowding. They found that reducing the number of low-complexity ED patients is unlikely to reduce the waiting times for other patients or ease overcrowding.

The fact that factors external to ED are major causes of ED crowding indicates that ED overcrowding is a systems problem. In order to understand the system perspective, we begin by focusing on the relationships between an ED and IU to clearly characterize the dynamic nature of their interaction.

1.2 Crowing Definitions

The Canadian Association of Emergency Physicians defines ED overcrowding as "a situation in which demand for service exceeds the ability to provide care within a reasonable time, causing physicians and nurses to be unable to provide quality care" (CAEP 2001). Asplin et al. (2003) adopted a definition from the American College of Emergency Physicians (ACEP 2002): ED overcrowding is "a situation in which the identified need for emergency services outstrips available resources in the ED". While these kinds of definitions make good common sense, they are not too useful for a practical use. Articulating an accurate and measurable definition that can be used as a decision base turns out to be much more difficult. As an example, US ED directors provided five different stand-alone measures (Derlet, Richards, and Kravitz 2001):

- Patient waits > 60 minutes to see physician
- All ED beds filled > 6 hours/day
- Patients placed in hallways > 6 hours/day
- Emergency physicians feel rushed > 6 hours/day
- Waiting room filled > 6 hours/day

Those metrics seem intuitive, but none of them captures both resource utilization and process times simultaneously, and are therefore not applicable as real time metrics. Jones et al. (2006) tested four real time metrics (READI, EDWIN, NEDOCS and EDCS) to conclude that none of the metrics is perfect. A combination of some parts of those metrics yielded good predictive power, but a site specific calibration would be necessary. Schull, Slaughter, and Redelmeier (2002) used an expert panel to find a list of drivers for urban ED overcrowding. The panel considered diversion status as an operational definition of crowding because it reflects the inability of providing emergency medical care to critically ill patients. Diversion status is well defined as a situation in which an ED does not accept incoming ambulances, diverting them to surrounding EDs. Use of ambulance diversion status as the definition of ED overcrowding, however, has its own problem: there is no commonly accepted function of measures which drives the decision to declare diversion status for an ED.

With this in mind for our experiments we chose to use our own real time crowding definition:

- 100% ER bed utilization and
- Queue length > 50% of ER beds.

This metric is insensitive to the size of the ED and represents a combination of resource stress and waiting times.

2 PROBLEM AND METHODOLOGY

2.1 Problem Definition

A simple discrete event simulation model of an ED-IU system is created to replicate the overcrowding phenomena, particularly the overcrowding caused by IU backlog. This simulation model is used to study the dynamics of overcrowding by varying key parameters. It allows for a more in-depth understanding of the crowding behavior of an ED in conjunction with an IU. Understanding the nature of ED-IU interaction, generated by this simulation study, can provide focus to administrators seeking to improve ED performance.

2.2 Conceptual Model of an ED-IU System

In order to clearly understand activities in ED, our study began with observation of a local hospital. Observation began by following patients from the main entrance, to the greeter, triage and registration into the ER. Second we observed human resources by shadowing a triage nurse, a physician, and an ER nurse. Third we stayed with different physical resources, such as the greeter desk, waiting room, triage rooms, adult ER, pediatric ER and Fast track. Those observations provided an understanding of what really happens in an ED and showed us the complexity of the department. The complexity in ED is mainly driven by the interdependencies between multiple goals such as efficient processes, quality of medical care and safety for everybody.

To concentrate our study on the ED-IU system we decided to use discrete event simulation (DES). The use of DES modeling has become a popular choice for studying EDs in the past decade (Jacobson, Hall, and Swisher 2006). DES allows a user to easily capture complex patient flows as well as evaluate the effects of new patient flow rules and policies. Although the patients arriving pattern and their illnesses are highly unpredictable, the test and treatment sequence is controlled by clinical staff. By changing processes in the ED-IU system it is possible to examine how to reduce waiting times and increase resource utilization rates.

Looking at a hospital as a system, the ED acts as a gate channeling emergency medical care patients into the

IU. At a macroscopic scale, ED-IU system can be described by a conceptual model of two stations without a buffer, with a branching point in between the two stations (Figure 1). Some of the system parameters such as patient influx, test times, and treatment times, are not predictable, and thus commonly used probability distributions are assumed for those system parameters.

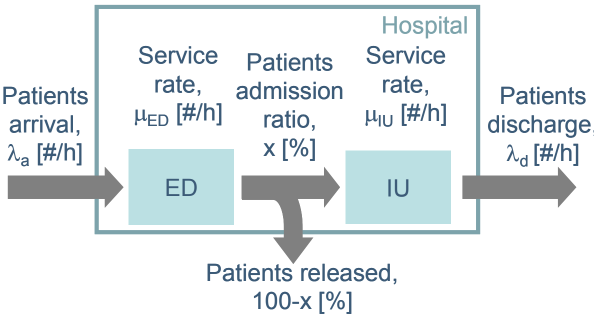

Figure 1: Two-station model without buffer

Patients arrive at the ED with the rate $\lambda_a(t)$ [patients/hour], which is a function of the time of day. The ED provides a service rate of μ_{ED} [patients/hour] independent of the time. The majority of patients (100-x) [%] are released from the ED, whereas the remaining x [%] are transferred to the IU. As there is no buffer between the ED and IU, boarding patients stay in the ED before their transfer into the IU. The IU provides a service rate of $\mu_{IU,}$ [patients/hour] which is also independent of the time. The patient discharge rate $\lambda_d(t)$ [patients/hour] is also assumed to be a function of the time of the day.

3 BUILDING A SIMULATION MODEL

3.1 The Flow Chart And Modeling

From the observations in the ED we drew a flowchart of the ED-IU system, which follows a similar format as the simulation model (Figure 2). A patient arrival module creates Walk-in patients as well as the Ambulance-in patients. Usually a patient's visit starts with the greeter desk then triage, registration and some waiting time in the ED waiting room. In our model those steps are merged in the waiting module "Patients waiting for ER". Then a patient is taken into the ER by a nurse and put into a bed. After a pre-examination and potentially some pre-testing by the ER nurse, the patient is seen by a physician, who examines the patient and orders tests or treatments. If the physician decides to release the patient, an ER nurse facilitates the release process and the patient leaves the ED. If the physician wants to send the patient to the IU a consulting physician from the IU clinic evaluates the patient and has to agree to his/her admission. Depending on the current bed availability in the IU, the patient is either transported to the IU immediately or has to wait in the ER for an IU bed to open. These boarding patients are reflected in the simulation by the waiting module "Patients boarding in ER".

While in the IU the patient receives tests and treatments. As soon as the patient is medically ready to be released he/she waits for a physician to execute the final examination and complete the checkout process. This is reflected in the waiting module "Patients waiting for discharge". Finally the patients are discharged from the IU.

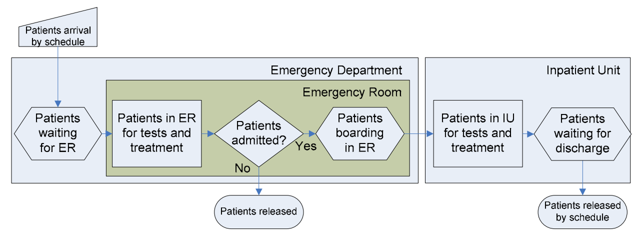

Figure 2: Simplified flow chart for patient flow in ED-IU system

In the model we used a process module for the ER with a separate queuing module, which represents the ED waiting room. A similar process module was used for the IU model; however there is no IU waiting module because the IU queue is accounted for, by boarding within the ER module. IU discharge occurs in a pattern over the day. To operate this discharge we assigned a process with a separate resource that is on a 24 hour schedule that follows typical, real discharge times. For the patient arrival we used a schedule as well, which was set to 24 hours and specifies the mean number of arriving patient entities in the system. Throughout the simulation we modeled ER beds, IU beds and MDs for discharge in use as resources.

3.2 Input/Output

The system variables used in the simulation model include process times, delay times and resources. As the ED-IU system inherently has a high variability in demand and process times, constant values for these variables would not be appropriate and thus the input variables are modeled as random variables with appropriate probability distribution functions. System variables and parameters used in our simulation are summarized in Table 1.

Table 1: Simulation input

Name	Distribution	Schedule	Value	Unit
Walk-In patients	Poisson	Yes	0 to 4	patients/hour
Patients admission ratio, x	-	No	20	%
ER beds	-	-	8	beds
IU beds	-	-	62	beds
Time in ER	Triangular	No	1 - 2 - 5	hours
Time in IU	Triangular	No	2 - 5.7 - 9.4	days
IU discharge	Poisson	Yes	0 to 4	patients/hour

The volume of walk-in patients was set to vary as a function of time of day. To do this we adopted an example of hourly patient arrival rates from Williams (2006). The schedule we used in the simulation, shown in Figure 3, represents the mean values of a Poisson arrival process for each hour. The values vary from a minimum of 0 to a maximum of 4 over the 24 hour period.

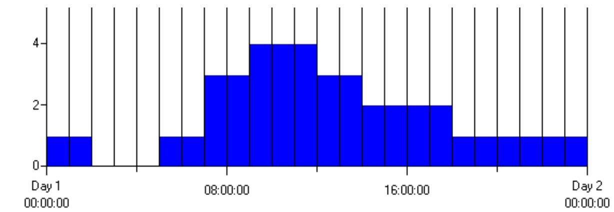

Figure 3: Walk-In patient schedule

The percentage of patients transferred to the IU, x, is a probability parameter in a decision module where the ED patients are designated to be sent to the IU or released from the system. The patient treatment times in the ER and the IU are assigned triangular distributions. For example, the treatment time in the ER ranges from a minimum of 1 hour to the maximum of 5 hours with the most likely value of 2 hours.

Another system variable of interest is the IU discharge pattern. The pattern is shown in Figure 4 and follows a Poisson distribution that is similar to the walk-in patients arrival pattern (Williams 2006).

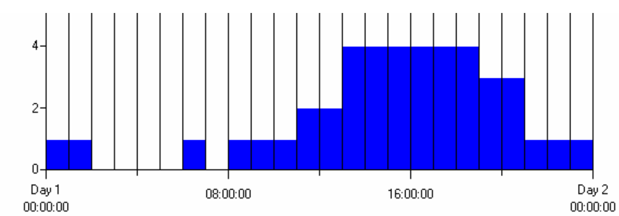

Figure 4: Discharge from IU schedule

The simulation outputs we chose to collect are the measures commonly used as key performance indicators of emergency care systems (Table 2). The "door to bed time" is the length of time from the moment a patient steps into the ED up to when he/she is placed into an ER bed. In practice "IU utilization" is often documented as the percent of occupied beds at midnight. However, the highest occupancy levels occur during the daytime and those values can differ up to 20% from the midnight calculation e.g., 70% midnight average vs. 87% midday average (MDPH 2001). Our simulation accounts for the IU utilization levels at each moment in time and calculates the straight average out of it. The "ER beds occupied by boarding patients" measure is calculated by counting the time each ER bed is occupied by a boarding patient per month and dividing it by the total number of ER bed hours per month. Finally, the "ED overcrowding" variable is counted using the criteria we set forth earlier (Section 1.2).

Table 2: Simulation output

Name	Calculation type	Unit
Door to bed time	Average	hours/patient
IU utilization	Average	%/month
ER beds occupied by boarding patients	Average	%/month
ED overcrowding	Sum	hours/month

3.3 Scenarios

To start the scenario analyses we set up an experiment with the standard conditions we observed at a local hospital. These conditions included a "Patient admission ratio" of 20%. We set the simulation to include a 30 day warm-up period followed by 30 days of tracking the key performance indicators. The long warm-up period was necessary to populate the IU with patients, because it was empty at the beginning of the simulation. Since "IU utilization" was not directly controllable in the simulation, we used "Time in IU" as a control variable which directly effected the "IU utilization". In order to verify that the "Time in IU" is a good proxy for the "IU utilization," we executed test runs that proved a strong positive proportional correlation. Each of the following set of values – [minimum, most likely, maximum] – was used for the triangular distribution for "Time in IU [days]" to control the "IU utilization":

- [4 – 5 – 6]
- [5 – 6 – 7]
- [5.5 – 6.5 – 7.5]
- [6 – 7 – 8]

3.3.1 ED-IU Coupling Analysis

The purpose of a coupling analysis is to replicate the ED overcrowding phenomena and in particular, its relation to IU backlog. To accomplish this, two key parameters were varied in our simulation study: the "IU utilization" and the "Patients admission ratio, x". We ran 6 scenarios with the "Patient admission ratios": {50%; 35%; 25%; 20%; 15%; 5%}. The patient admission ratio represents how tightly the ED is coupled to the IU. For example, at 0%, the two subsystems are completely decoupled and thus the ED is not affected by the IU's state. At 100%, on the other hand, the ED's crowding state is directly affected by the state of the IU. To emphasize the role of this factor in ED-IU dynamics, we refer to it as ED-IU *coupling factor*. Each scenario ran 100 times for each "Time in IU" distribution in order to populate the wide range of different "IU utilizations" from 55% to nearly 100%. All the input values for this test are shown in Table 3.

Table 3: Input values for ED-IU coupling analysis

Scenario [%]	Runs	Time in IU [days]	
		Most likely values (mlv)	Width of distribution
50	500	2.0, 2.3, 2.5, 2.7, 3.0	mlv-1 / mlv / mlv+1
35	500	2.5, 3.0, 3.5, 3.7, 4.0	mlv-1 / mlv / mlv+1
25	500	3.5, 4.0, 4.5, 5.0, 5.5	mlv-1 / mlv / mlv+1
20	400	5.0, 6.0, 6.5, 7.0	mlv-1 / mlv / mlv+1
15	600	6.5, 7.0, 8.0, 8.5, 9.0, 9.5	mlv-1 / mlv / mlv+1
5	400	20.0, 25.0, 27.0, 28.0	mlv-1 / mlv / mlv+1

3.3.2 ED Improvement Analysis

We expected that improving ER efficiency and improving IU efficiency will have different impacts on crowding levels, with the magnitude of this difference depending on the IU utilization regime in which the system is operating. To verify this, we ran 3 scenarios, one with the standard ER conditions, one with the "Time in ER" varied by approximately +20% from the standard condition and one varied by approximately -20%. Each scenario was run 300 times to gather results for IU utilization levels from 55% to nearly 100%. All the input values for this test are shown in Table 4.

Table 4: Input values for ED improvement analysis

Scenario		Fast ER	Medium ER	Slow ER
Runs		300	300	300
Time in ER [hours]	Most likely values (mlv)	1.5	2.0	2.5
	Width of distribution	mlv-1 / mlv / mlv+1	mlv-1 / mlv / mlv+1	mlv-1 / mlv / mlv+1
Time in IU [days]	Most likely values (mlv)	4.7, 5.7, 6.7	4.7, 5.7, 6.7	4.7, 5.7, 6.7
	Width of distribution	mlv-3.7 / mlv / mlv+3.7	mlv-3.7 / mlv / mlv+3.7	mlv-3.7 / mlv / mlv+3.7

3.4 Assumptions and Simplification

While designing our experiment the following assumptions and simplifications were made:

- Walk-in and ambulance-in patients are combined in Patients arrival
- All patients leave the ER by transfer to the IU or are released – i.e. no transfers to other IUs, no deaths, and no direct transfers to the Operation Room were taken into account.
- All patients leave the IU by discharge – i.e. no deaths or transfers were taken into account.
- No different entity types were created in order to distinguish between different acuity levels patients.
- The IU takes all its patients through the ER – i.e. no admission through appointments.

These assumptions may cause a deviation between the actual numbers generated by our experiment and real life numbers. However, since the general model's logic is accurate, we believe that the trends, shown by the scenarios, remain useful.

4 RESULTS AND DISCUSSION

4.1 Results

The standard condition scenario created a cloud of results from an "IU utilization" of 55% to 98%. The data is represented in Figure 5 with "IU utilization [%]" on the X-axis and the "ED overcrowding [hours/month]" on the Y-axis. In order to create the displayed trend-line we computed an average of simulation results for an area of 0.25% left and 0.25% right of a point and calculated a moving average of 9 data points. Figure 5 clearly shows a positive correlation between the IU utilization and ED overcrowding, which should not be surprising, however it is worth noting that the positive correlation occurs only after the IU utilization is significantly high.

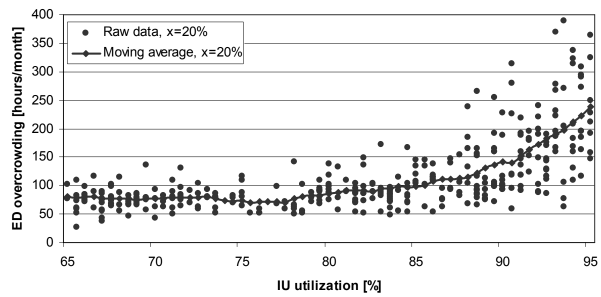

Figure 5: Results of standard conditions scenario

4.1.1 ED-IU Coupling Analysis

The results of the coupling analysis simulations are shown in Figure 6 as a moving average like in the standard scenario.

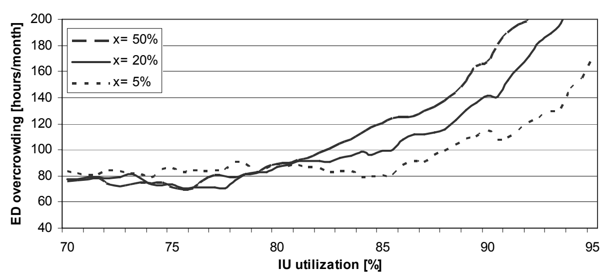

Figure 6: Results of ED-IU coupling analysis – effect of the coupling factor on the relationship between ED overcrowding and IU utilization.

In this analysis we wanted to learn about the responsiveness of overcrowding to the variation of the two key factors "IU utilization" and the "coupling factor". Figure 6 shows that at the same IU utilization, a higher coupling factor results in more overcrowding. Using the same data as Figure 6 we were able to display the relationship between the "Patient admission ratio" and overcrowding. To do this we held "IU utilization" constant, and placed the "Patient admission ratio" on the X-axis (Figure 7). Each dot in the diagram is the average of the scenario results from 80%-90% IU utilization. Those utilization values seem reasonable with our definition (Section 1.2) and empirical numbers, which are in this region (MHPF 2001; MDPH 2001). The results show a clear positive correlation between "x" and "ED overcrowding".

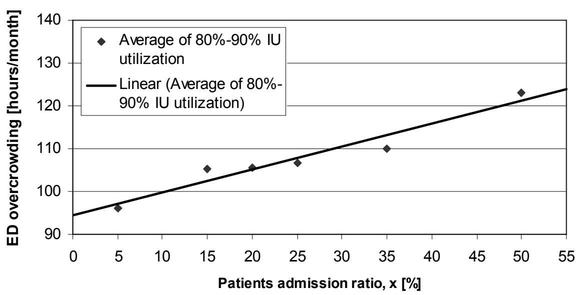

Figure 7: Results of ED-IU coupling analysis – constant IU utilization

4.1.2 ED Improvement Analysis

The results of the ED improvement analysis are presented in Figure 8 as a moving average like in the standard scenario. As expected, changes in the efficiency in ER – i.e. shorter or longer time in ER – shifts the curve up or down, but does not seem to affect its shape.

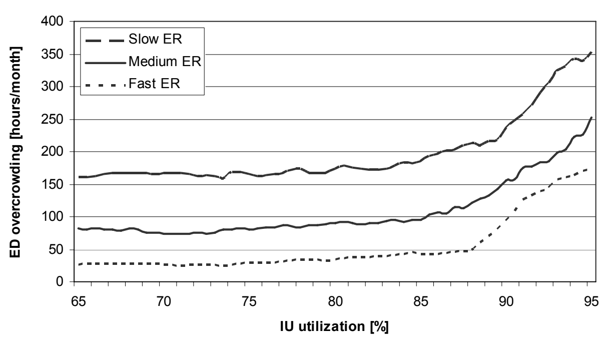

Figure 8: Results of ED improvement analysis

4.2 Discussion

It is typical for queuing systems to have a positive exponential correlation between the utilization and waiting times (Odoni 2004). The plot of the standard conditions scenario (Figure 5) shows the same tendency, meaning that, for higher IU utilizations ED overcrowding shows higher sensitivity to the IU. The results do reflect the common perception that ED crowding is due to IU backlog: when the IU is crowded, the ED is more likely to be crowded and the crowding tends to be more severe. When the IU is not busy, the ED is insensitive to the IU, and its crowding is more likely the result of its own operational issues.

4.2.1 ED-IU Coupling Analysis

The coupling analysis was intended to test the effect of different "Patient admission ratios" on the behavior of the ED-IU system. Figure 6 shows the curves for three different ED-IU couplings {5%, 20% and 50%}. It is notable, that the transition point between the non-IU-sensitive and the IU-sensitive area shifts to the left with higher coupling factors. Also as we progress from 5% to 50% Patient transfer rates the curve approaches a proportional relationship. It seems that the coupling percentage is an important variable in understanding the system behavior. In other words, if an ED needs to transfer a higher portion of its patients to its IU – i.e. significantly coupled – then it will be more affected by the state of the IU. On the other hand, if few patients are transferred to the IU – i.e. loosely coupled – then the ED tends to act as an isolated unit from the IU. In both cases, the ED becomes sensitive to the state of the IU only when the IU utilization is significantly high.

The effect of the coupling factor becomes much more evident by plotting ED crowding as a function of the patient admission ratio (Figure 7). We chose the 80-90% IU utilization regime for the plot because that is the effective IU utilization where many hospitals operate (MHPF 2001; MDPH 2001). In that regime the ED-IU coupling seems to have a linear relation to overcrowding.

This result can be used to compare hospitals' ED overcrowding hours with respect to their different patient profiles (fraction of transferred patients). Even when hospitals have the same IU utilization rate, their EDs may feel dramatically different pressure from the IU depending on their patient profiles. This effect is driven by the strong correlation between high acuity level and probability for IU admission.

4.2.2 The Transition Point And Implications

Having another look at Figure 6 and keeping in mind that the utilization of IUs is typically around 80-90%, it becomes clear that most EDs operate in the region of the transition point. In a case of above-average IU utilization, the crowding is mostly determined by IU backlog and relieving pressure in the IU would have a critical effect in lowering ED crowding. Thus, we call this regime, where the IU utilization is above the transition point, IU-limited. On the other hand, if IU utilization is a little below average, the ED crowding becomes mostly independent from the IU. In this region, lowering IU utilization does not affect ED crowding any longer, which leads to a conclusion that the ED itself is acting as a bottleneck; we call this regime ED-limited. An understanding of this can guide decisionmakers in properly concentrating their efforts on effectively improving the performance of the overall ED-IU system, instead of focusing on an individual ward. If the IU utilization in one's hospital is relatively low, then high-priority effort should be put towards things concerning the ED itself. If the IU utilization is high, then effort should be focused on the IU or both (e.g. transfer processes, standardization, etc.).

4.2.3 ED Improvement Analysis

It is obvious that shortening the length of stay in an ER –i.e. improving the efficiency in ER's operations – does reduce crowding. The scenario results verify this and show that efforts towards improving ER processes in the ED would result in less crowding hours regardless of in which regime the system is operating. On the other hand, the behavior of the system – i.e. the extreme sensitivity in the IU-limited regime – remains the same irrespective of the efficiency of the ER. Given a large variation in ED crowding in the IU-limited regime (Figure 5), improving the efficiency of the ED alone will have a limited impact. Therefore it is important to balance the effort to improve the system in both regimes to obtain the maximum effect on the system as a whole.

5 CONCLUSION AND FUTURE WORK

In this study, we used discrete event simulation to model the relationship between an ED and its associated IU. This model provided data relating ED overcrowding to IU utilization, coupling between the ED and IU, and ED efficiency. From the data we found that most hospitals operate at a transition point between an IU limited regime and an ED limited regime. Therefore, when attempting to improve ED operations one must take both regimes into account and understand which will have a greater effect on their hospital based on that hospital's particular IU utilization level. However, it is important to note that the IU limited regime has the potential to cause more extreme crowding and focusing on this regime may have greater impact on the system.

In order to further validate the results of this study, a more accurate simulation model could be used as well as an empirical study. The use of a high fidelity simulation model would provide the possibility to test different ED-IU system improvement ideas. Those future studies will be put in the context of this study by relating to the different improvement potentials within the ED for ED-limited regime improvements and the IU for the IU-limited regime improvements.

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