To Cross the River Styx:

an exploration of patient flow through the intensive care unit

Jeff Kahn, Agent Based Modeling, Spring 13

An Agent Based Model of Patient Velocity through the Medical ICU

I designed and implemented an Agent Based Model of patient flow through Intensive Care Unit (ICU) system. My goal is to explore the dynamics behind patient velocity through the ICU and create a model which can be extended upon further. I plan to explore the dynamics by attempting to grow the underlying mechanisms by which the ICU overflows. ICU overflows occur when all ICU beds are full and there is patient required ICU care. ICU overflow leads to a great deal of logistic overhead and cost. Therefore, the model will explore how personnel and patient acuity lead to overflow situations in the ICU.

Motivation

ICU care is costly. Many studies suggest that 11-30% of hospital costs and .4-2% of GDP result from delivering ICU care. Further, the number of beds in the ICU has increased by 26% since the 1980's.[1] In addition, the complexity of care delivered in the ICU suggests a high variability in patient throughput.

Fluctuating, uncontrolled throughput is also costly. In an interview with an ICU third year fellow at Northwestern Memorial Hospital (NMH), the cost of one ICU day without procedures can be anywhere from $2500-$3000. Of course, this cost is much higher during overflow

1 Halpern NA et al. Critical care medicine in the United States 1985-2000: An analysis of bed numbers, use and costs. Critical Care Medicine 1999. 32(6):1254-59

situations. This high economic cost suggests that the ICU is an opportunistic place to analyze the mechanisms that cause patient overflow.

Patient Overflow

Patient overflow is defined as any time a patient requires ICU attention but cannot be placed in the ICU because all the current beds are full. Patient overflow causes hospital wide issues.

First, a patient overflow in the MICU causes potential harm to the patient because their caregivers are providing care in an unfamiliar environment. This means that the either the care giver isn't used to delivering care to this type of patient. Eg. a medical floor nurse is caring for a critically ill patient requiring specialized ventilator assistance. Or, this means that the nurse does not typically deliver care in that unit. In this case, an ICU nurse might be floated to another unit where they have open beds. This can be detrimental to care because the nurse does not understand her resources.

Second, it reduces the number of nurses in the MICU because a single nurse has to be floated to the location of the overflowed patient. Third, it takes time away from the patient throughput coordinator and and charge nurse to coordinate where the patient is and the strategy to get the patient back to the MICU. Fourth, it requires that physicians travel further to see the patient increasing non-productive travel time. Fifth, the patient occupies a room in a different ICU which can cause logistical issues for the other ICU. Sixth, I observed that overflow caused nurse morale issues because they felt uncomfortable being in a different ICU. Because of these issues, I am considering patient overflow to be a surrogate metric for system breakdown.

One example of a process affecting patient velocity is the patient discharge process. This is the process that all patients go through to leave the ICU. Discharges happen during morning rounds at 7 AM. Patients are visited based on arbitrary heuristics like physician proximity to patient. For a patient to be released, the attending physician must observe and sign off that the patient is in stable enough condition to be released to another location. Most often, the patient is released to the medical floor or a long term care facility. This seems to cause flow issues because patients can enter the ICU at any time of the day while patients can only leave during the short time windows.

Specifically, if the patient has been released to the medical floor, the patient's record must be viewed by the intake physician on the medical floor. For transport to take place, there must be an available bed in the receiving unit. In addition, transport of the patient depends on the availability of a transporter. Long term care facilities must also be pre-arranged so the patient can be transported. However, I am not as familiar with the procedure in place to transport to a long term care facility. This requires more investigation

What Can we Learn

With this model, will aid in understanding more about how patients move through the ICU and identify key variables in preventing overflow and increase patient velocity. It will also serve as a foundation on which literature can be computationally tested and questioned. For example, we might learn that patient flow is unaffected by how sick patients are or that the number of caregivers does not affect patient flow or that overflow happens because the ICU is too complex of an environment.

More succinctly the driving question is as follows: what key factors determine patient flow and overflow in the ICU? And how can we grow the patient overflow dynamics seen in ICU census data from the simplest components?

I plan to initially set up the model in general fashion based on literature findings so the results may be externally valid to other ICU settings. Note that each ICU is a unique system. Each ICU has a patient input source, provides care, and discharges patients, but each ICU varies on how these sources are configured. A prime example of this exists between a large academic medical center ICU like Northwestern Memorial Hospital and a rural ICU in North Central Iowa. At NMH, the sickest patients are transported to NMH to be healed whereas the ICU in North Central Iowa may be transporting their sickest patients out.

A Guide to Implementation

Who are the Agents(Properties | Actions):

1. Patients (initial-apache apache acuity TTL LOS stable-ticks my-caregiver receiving-care? care-count death-prob bed-number | die, improve health, decrease health)

2. Care-givers (my-patients, treat-count, acuity-score | treat-patients, discharge patients)

System Parameters

1. Daily Patient Arrival Probability Distribution
2. Number of beds
3. Number of care givers

4. Number of patients overflowed
5. Patient acuity distribution
    1. Death probability based on acuity ranking
6. Direct Care time
7. Time to Live information[2]

Time-Step (hour)

1. Patients flow in to the ICU with probability based on the hour of the day

2. The new patients are assigned care-givers

3. Care-givers treat their patients. If I have two patients, I split time between each of them.

4. Patients either improve their health or decrease their health based on the quality of care.

5. Depending on how sick I am, there is some chance that I die

6. If I have been healthy for set amount of hours or days, I am ready for discharge at 7am

Measures

1. Patient release time distribution
2. Average patient release time
3. Average cost per day
4. Bed Utilization 1- (total empty bed time / total elapsed time)
5. Patient Throughput (total patients out / # of days)
6. Number of patients overflowed

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[2] Naved,, S., Siddiqui, S., Khan, F. (2011). APACHE-II Score Correlation With Mortality And Length Of Stay In An Intensive Care Unit. Journal of the College of Physicians and Surgeons Pakistan, 21(1), 4-8.

Rationale for Choices

ABM is an effective modeling choice for this application because it provides "an object to think with" as well as a heterogeneous and uncertain environment of interest. The ICU has many independent, interacting actors that engage on an individual level. We are primarily concerned with how individual agent "micro-motives" correspond to the observed "macro-behavior" in the ICU.

I plan for this model to provide insights into the underlying mechanisms of patient release times in conjunction with physician rounds. This is helpful because this model can serve as a glass box where every involved stakeholder can question the assumptions. Health care often exhibits what some call system inertia because of the necessary coordination of all involved stakeholders. I plan to be able to present my model in a few minutes inviting feedback and improvement from all stakeholders including: top management, MICU director, MICU staff, Medical Floor staff and Medical Floor Physician. The transparency and ease of understanding of the model will provide all empower all interested stakeholders to take part in process improvement.

Beyond its value in facilitating communication, the computational nature and ease of extendability will allow others to build off the model to understand tangential phenomena. This also means that the model can be improved by integrating real hospital data into the model.

Agent Based Modeling of this phenomena has several distinct advantages over alternative simulation methods. First, many model paradigms require extensive data collection and can take years to process the health data in a way suitable for simulation. In addition, health data is notorious for being difficult and lengthy to process. Second, other modeling paradigms like monte carlo simulation or discrete event optimization do not allow interested stake holders to gain insight from the model construction itself. Specifically, interested stakeholders have to rely more on the modelers to have correct assumptions. With ABM, the assumptions are clear and up for debate.

The current model to analyze the operational effectiveness of patient flow is often judgement based that depends on expert judgement and assumptions made on aggregate statistics. While timely, expert judgement often comes feeling and experience rather than a stated assumption. To me, it appears exceedingly clear that Agent Based Modeling will aid in the understanding of patient flow through the ICU.

There were also a few key decisions I made with regards to the model. First, was a decision to abstract acuity as an APACHE score. Many ICUs use this measure as a benchmark of their performance and has many successful years in the field predicting aggregate mortality rates. Second, I chose also to abstract the treatment process using quality of care score which says that the more you are seen by a caregiver, the more likely your health is to improve. However, given the critical conditions of the ICU, we still see death and abrupt decreases in health status. Third, I abstracted doctors and nurses of different status and experience all as uniform care givers. Based on observations, it appeared that the care was not healing the patient in the ICU but rather giving the patient the best chance to increase his or health and survive.

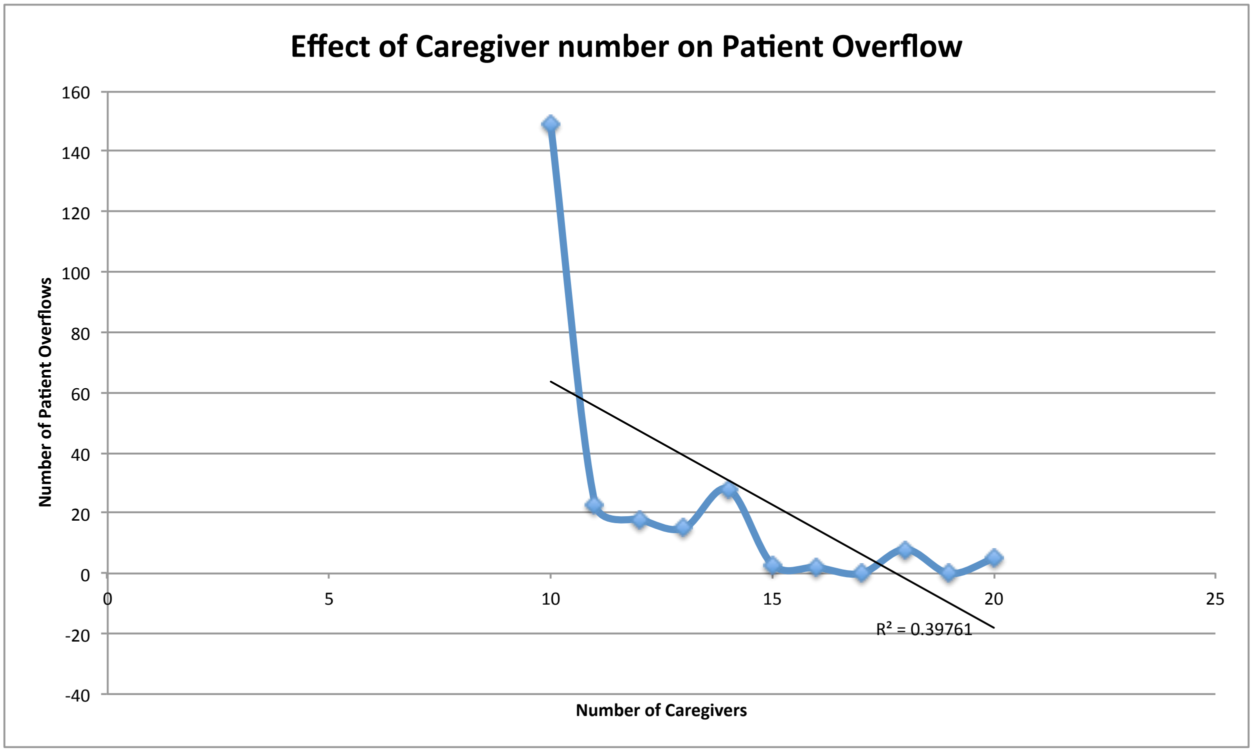
These abstractions helped narrow the focus on the essential ingredients: inflow, care, outflow.

Analysis

ICU care is complex for many reasons. This analysis will first focus on the model results using behavior space and qualitative analysis and secondly focus on the modeling process to uncover the reasons for complexity.

As with any model, we must asses its limitations. Since this netlogo model only approximates the environment of an ICU, we must understand the results in context. Further, as is mentioned earlier in this report, the ICU setting is dependent on its location. I do believe, that given the right inputs this model should be externally valid to any ICU location.

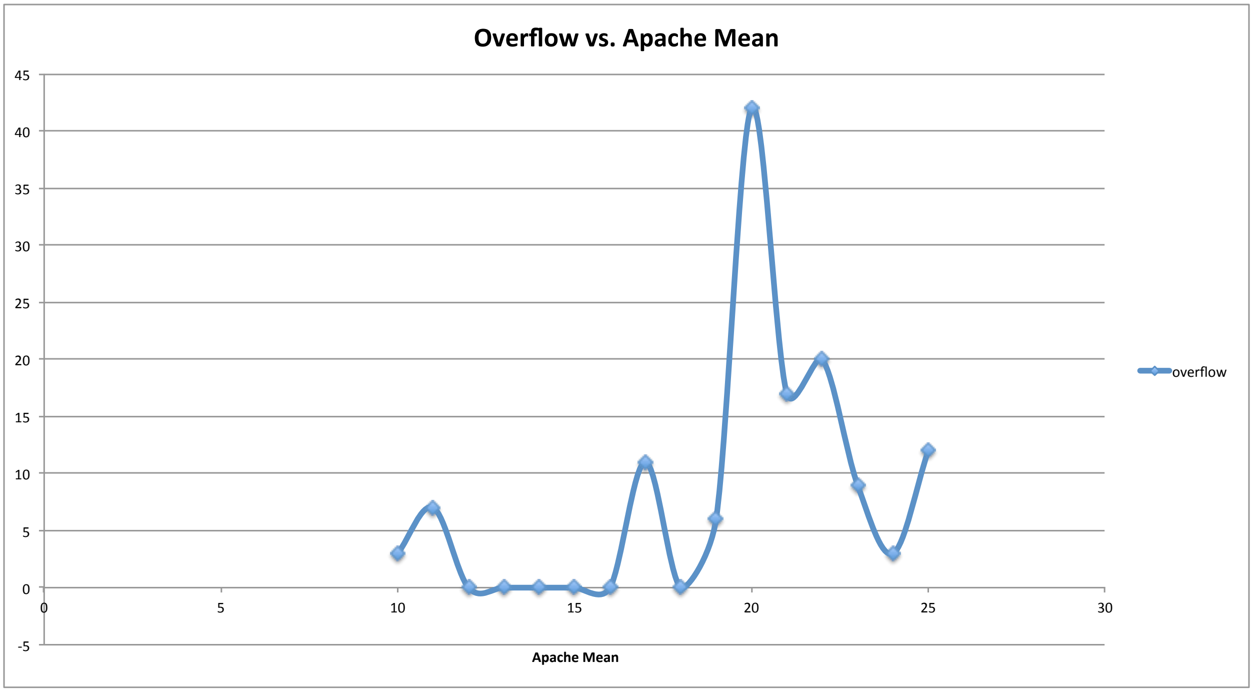
I used behavior space to systematically identify trends in the parameter space as well as path dependence and critical points. One example of trends and critical point is illustrated in the chart below.



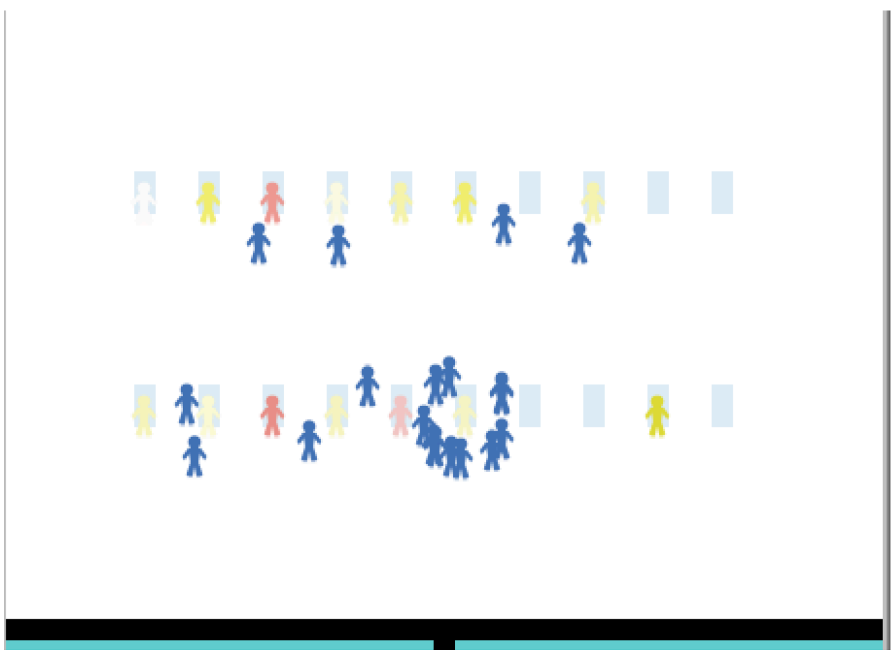
This is a graph of the relationship between the number of caregivers and the number of patient overflows. We generally observe an inverse relationship; as the number of care-givers increases the number of patients overflowing decreases. Much more interestingly, this illustrates a critical point where increasing from 10 to 11 caregivers, holding the rest of the parameter space constant, corresponds to a marked decrease in the number of patient overflows. This result is interesting in that literature and common knowledge have often cited hiring more caregivers decreases patient overflow.[3] Here we see that depending on various staffing factors, hiring more care givers may not be the mot effective use of resources. This behavior space assumed that all the care-givers time was spent caring for the patient.

Another important parameter is how sick patients are in the ICU controlled by a normally distributed apache score. The next behavior space will look at how varying the apache-mean slider affects number of patient overflows.

3 Patient Flow in Hospitals:Understanding and Controlling it Better. Carol Hararden, Roger Resar, Frontiers of Health Services Management, 2003



Here we see an interesting



relationship between patient overflows and apache mean. Qualitatively, we see that increasing the apache mean to a certain point does not have any effect on patient overflow until it hits a critical point where overflow dramatically increases. At this point patients are sick enough to stay alive and take the time of caregivers but not so sick that they die immediately. As the apache mean increases, we begin to see a fall in the overflows because at this point patients in the ICU are so acute that they die before taking up beds. This result helps to prove the macro validity of the model because empirical literature has shown the existence of this relationship.[4] However, the advantage of the ABM approach is that we can grow the results from clear rules and assumptions rather than analyze and speculate retroactively. This particular data also suggests that each ICU may have some critical mean value of apache scores where overflows are highest. This could lead to strategic management changes by triaging patients even further in the ICU which could help reduce the acuity of patients in the ICU and lead to decreases in patient overflow.

Qualitative Analysis

4 Intensive care unit length of stay: Benchmarking based on Acute Physiology and Chronic Health Evaluation (APACHE) IV*, Zimmerman et al., Critical Care Medicine 2006

Qualitative analysis of the flow model also suggests some face validity and important insights. In this scenario we have a group of care-givers swarming around a newly admitted acute patient. This is similar to the case if a patient presents a medical adverse event somewhere in the hospital and is brought to the ICU. Instead of one caregiver, there will be many attempting to stabilize the patient. Some of the time, these acute patients die, other times they quickly stabilize and survive. However, you can observe from watching the model in this parameter space with many caregivers that having these caregiver teams appears to shore up local acuity issues very quickly. The more quickly acute patients can be stabilized, the quicker the bed can open up for a new patient. This analysis suggests that it might be worthy to investigate the effectiveness of acute response teams in a critical care environment.

Further Validation and Verification

I attempted to validate and verify my model concurrently with development. I began the process by identifying key pieces of literature and performing empirical research at Northwestern's MICU. The literature and empirical process helped identify the key variables of patient flow and put context to the relevant literature.

In extending this project, it would make sense to further validate this model against literature and calibrate the model against one specific ICU to see how well the model generates similar dynamics.

The ABM Process and Conclusion

I thoroughly enjoyed the quotes presented at the beginning of each ABM chapter. One quote that specifically speaks to me after going through this process Epstein in 1999 saying "If you didn't grow it, you didn't explain it". That speaks to the power of the ABM process both as a learning tool and as a research tool. Being forced to make and publish sound assumptions and formalize fuzziness and then failing and improving, hones the understanding of the phenomena under analysis. It is this process of constantly asking why and how that ABM seeks to understand.

This process has inextricably proven the value of this process as a way of thinking and interpreting the world. Thorough Agent Based Modeling is informative, challenging and guiding, but the process leaves the modeler a clearer, more sound thinker.