An Exploration into the Uses of Agent-Based Modeling to Improve Quality of Health Care

Ashok Kay Kanagarajah, Peter Lindsay, Anne Miller, David Parker
ARC Center for Complex Systems
University of Queensland, St Lucia, Queensland, Australia

Abstract

Health care is a complex adaptive system that is difficult to analyze for the purpose of improving work performance. This paper discusses complex systems architecture and an agent based modeling framework to study health care system improvements and their impact on patient safety, economics and workloads. Here we demonstrate the application of a safety dynamics model proposed by Cook and Rasmussen[4], to study a health care system using a hypothetical simulation of an emergency department as a representative unit of a health care system and its dynamic behavior. By means of simulation, this paper demonstrates the nonlinear behaviors of a health service unit and its complexities; and how the safety dynamic model may be used to evaluate various aspects of health care. Further work is required to apply this concept in a 'real life environment' and its consequence to societal, organizational and operational levels of health care.

1. Introduction

Patient safety, acceptable workloads and economic imperatives are interdependent dynamic forces that often come into conflict in healthcare environments. For example, reducing the total number of available doctors could lead to increased work load for individuals causing fatigue. This could lead to oversight of tasks and eventually affect patient safety. Balancing these competing forces is increasingly a major pre-occupation of government regulators and senior hospital managers. Cook and Rasmussen[4] have developed a 'safe operating envelope model' as a useful tool in analyzing the balance between patient safety, economics and workload on a health care system (Figure 1.) In this model patient safety is a dynamic property of the dynamic system. We have chosen Cook and Rasmussen's model as it can be applied at any scale of a system to explain the consequences of different configurations of workload and economic forces and their implications for health care and patient safety.

Analysis based on the safe operating envelope model also lends to agent based modeling (ABM) simulations that can be used to further explore complex adaptive behaviors in environments such as healthcare. In this paper we use an Emergency

Department (ED) as a representative scenario to computationally demonstrate that the effect on safety depends on short time scale fluctuations in workload and loose coupling of 'resource buffers'. We will also discuss the effect of efficiency improvements within this organization driven by managerial and technical changes and work saturation, such as a bed-gridlock in an ED. The 'bed gridlock' or 'bed block' in an ED, is a situation within hospitals where patients stay in the waiting room for a treatment-bed despite having completed arrival in the ED for treatment. Waiting is due no beds being available within the ED.

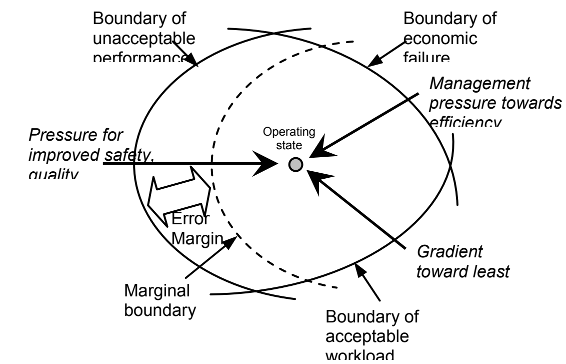

Figure 1: Rasmussen's modified safety dynamic model

2. Health Care Delivery System as a Complex Adaptive System

Health care delivery systems have been defined as Complex Adaptive Systems (CAS)[1,2,10,11]. They interface directly with the public and are open systems that demonstrate non-linear dynamics. Due to the socio-technical nature of health care, its boundaries are difficult to determine and the decisions are ultimately made by 'observers'. The observers of health systems show adaptive behavior; however, there are not always immediately apparent prescribed control mechanisms. A health care system can also be considered as a highly connected network of formal and informal nodes that adapt by learning through various 'experiments in progress '.The interdependent and networked nature of health care means that the activities undertaken in one node, say an Emergency Department (ED), have the potential to affect behavior in other nodes and across the network overall. Given the complex nature of a health care system, it may be difficult for managers to accurately predict the effects of actions, such as performance improvement and their system-wide consequences.

An Emergency Department (ED), for example, is a unit node within a health care system. It is relatively self-contained, non-trivial and of sufficient complexity as a setting for developing a dynamic model of healthcare as a complex adaptive system (CAS). Like all complex systems, the ED can appear simplistic at an appropriate scale, both within a time period and as a complete system. From the organizational perspective, the ED operates at physical, organizational and societal levels, as described in a generic health care system as depicted in Figure 2.

At the lowest level of the conceptual model, is the tangible layer (operational or execution layer) of a health care system. It has domains of different care processes, such as preventive care, interventional care, viability care and terminal care [6]. It can also be considered from a geographical perspective depending on the demographics and location of the care institution. Patients come into the ED and undergo a diagnostic process and a range of possible treatment modalities before they are discharged back into the community or admitted and transferred to another specialist ward. ED principally fits into interventional care. However, it may also be an initial contact point for preventive and terminal care services. The middle level of Figure 2 is an organizational layer. At this level, the care system manages a number of patients simultaneously; supplying line management and allocating appropriate resources. In this layer, economic and socio-technical aspects influence the operational functions. The societal level is the highest level. At this level, health care is affected by epidemiology, cultural, political and demographic characteristics of the community.

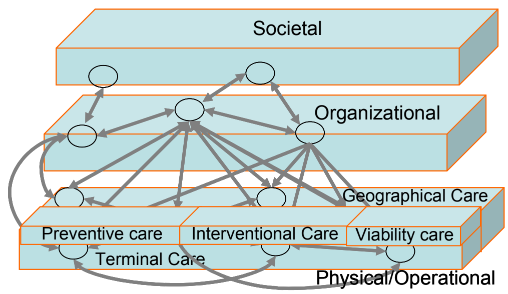

Figure 2: Structure of the health care system

The primary objective for the ED is to meet the needs of patients, as and when they arrive, and categorizing patient arrivals based on severity (triage). A major challenge for ED managers is to ensure that resources are kept available for unexpected increases in patient demand that may result from a range of environmental and socially mediated factors - , for instance, a flu epidemic, or a major accident resulting in multiple casualties. In these situations ED managers need crisis management plans or are able to send a signal to organizational and societal levels to develop alternate response processes.

3. Choice of Modeling Approach

There are numerous research and commercial articles within the literature of modeling and simulation of health care systems. June[7] and Fone[5] provide a good overview of health care simulations. Koelling[8] classified the available simulations as follows:
Systems: Strategic and policy studies, typically within organizations, at the regional or metropolitan area levels to study impact on organizational levels.
Health Systems: Strategy and policy studies at regional or national levels looking to develop policy.
Clinical: These simulations typically model work carried out on patient issues and are mostly led by medical practitioners.
Delivery: Tactically focused studies typically centre on a single facility or a department within a unit, and emphasize patient flow characteristics.
Prevention Studies focused on the prevention of illness, disease, or incidents; and the impact of prevention strategies and tactics that generally involve some type of clinical research.
Epidemiology Studies focused on the spread of illness or disease or the physiological understanding of an illness or disease.

While the boundaries within the above categories are blurred, there is a need to make assumptions that will make the modeling realistic. If these assumptions do not hold true, then the models that are generated may provide unrealistic answers. The implications of this situation are:

1) the simulation work carried out is very specific to particular situations
2) extrapolation beyond the modeling assumptions leads to unrealistic results
3) the time, money and resources invested are only useful to its specific purpose.

The purpose of our overall research is to develop a modeling framework for simulation applications that allows clinicians, managers and policy-makers to test the effects of potential actions given the dynamic relationships defined within the safe operating envelop model. Such an application should be based on contemporary theory about complex adaptive systems and use adaptable simulation tools such as ABM simulations.

Common simulation tools used in this area have been Discrete Event Simulation (DES) and System Dynamics (SD) modeling, which has several extant publications in ED or Health Care simulations [9]. DES uses patient flow models, and thus requires detail-level modeling. This tends to pose challenges in acquiring data due to detailed-granularity. Conversely, the SD models are aggregated models which do not look at patient flows, but require data at the level of patient classes. Brailsford[3] outlined and discussed both DES and SD as useful tools, but with limitations, depending on the type of issues being addressed; and noted that they are complementary to each other. She also highlighted that there is a need for an integrated approach using a unified framework from a conceptual and implementation perspective.

Hence in this paper we explore an ABM approach and develop an integrated simulation model that, when fully developed, will become an important decision support tool to deal with internal inefficiency issues within the operational-level of health care (e.g.; within the four sectors of ED). Moreover, it will support greater understanding of system-wide factors beyond the immediate control of the operational layers (e.g. outside the domain of ED managers).

4. Model Development - Agent Based Modeling of an Emergency Department

This section describes an agent-based model (ABM) of an Emergency Department (ED) and illustrates our approach by showing how an elementary model can be applied for complex analysis, while also revealing important insights through Cook and Rasmussen safety dynamics model.

It may be useful here to consider the ED in isolation to simplify the modeling task. ED simulation agents are the resources available within ED and consist of patients, doctors, nurses, technicians and treatment rooms and managers. An overall healthcare delivery system would contain many more agents than used in this simulation, but the dynamic interactions would be similar. We illustrate this with the following two examples:

1) The patients arrive at ED. This is a simplified stage of an agent, however, within the larger scope of a whole of health care model the patient arrival will

be a function of what happens within the society and will depend on the number of options that are available for those patients to receive treatment.

2) Transfer out to other wards will depend on the availability of appropriate beds in other areas. We demonstrate this by introducing a stochastic function to generate the bed availability for transfer.

Within the ABM at each time intervals agents execute behaviors. The goal of the agents in the model is to manage patient outcomes while minimizing preventable adverse patient events such as delays that increase the risk of secondary complications with subsequent increases in length of hospital stay. It is assumed that any patient who stays longer than 4 hours in ED before being diagnosed and treated will be counted as a potentially adverse event. This situation could occur for several reasons, such as lack of available treatment rooms or lack of availability of any of the single or combination of agents such as doctors, nurses and technicians.

Agents have elementary rules, for example;

- Patients are attended to, based on the criticality of their condition.
- Agents are self directed. i.e. doctors and nurses work as required, although the time they spend with the patients may vary depending on demand pressures such as the numbers of patients and severity of patient illness.
- Agents reflect adaptive behavior, based on the stage of other agents. For example, doctors may work faster or work over lunch periods in order to reduce excessive queues in waiting room. The opposite may also be true, however.

Work process

Arriving patients are categorized into different severity levels by the Triage Nurse, with Level 3 patients being more critical than Level 1 and 2. Level 3 patients are taken to an ED major room immediately upon arrival. Once in the room, they undergo diagnosis and treatment. Finally, they complete the registration process before being either released or admitted into the hospital for further treatment. Level 1 and Level 2 patients first sign-in with a registration clerk and their condition is further assessed by a Triage Nurse, before being taken to an ED room. Depending on their criticality this location may be to major room or minor room. Once in the room, Level 1 and 2 patients complete their registration, before receiving treatment. Finally, they are either released or admitted in to the hospital for further treatment. The treatment process consists of a secondary assessment performed by a nurse and a physician and the appropriate tests are performed by specialized technicians. Further treatment may be performed by a nurse or physician.

For Level 1 and 2 patients, the registration process is performed by a clerk with activities such as data collection, payment related information and entering the basic detail of patients into a medical chart for future reference.

The simulation model under development is built on a Microsaint Sharp® platform. Microsaint Sharp® allows the development of agent-based simulation models where multiple entities can be made to stochastically respond to conditions in their local environments, mimicking complex large-scale system behavior. Within the ED simulation, we have nominated critical agents such as: patients, doctors, nurses, clerks and technicians, and treatment rooms for acute patients (major rooms) and others (minor rooms). Although these resources are not comprehensive, they are aware of (and interact with) their local environment through elementary internal rules for decision-making, movement, and action, and allow study of the complex behavior at a conceivable scale.

Hypothesis testing

Cooks and Rasmussen's model explores how operating pressure gradients push the system's measures away from the boundaries of economic failure and work overload, towards the unacceptable performance (accident) boundary. Stable low-risk systems operate far from this boundary, and stable high risk systems operate nearer the acceptable margin. But the operating point moves in small increments and remains largely inside the marginal boundary. Unstable systems (otherwise known as chaotic systems) have large rapid shifts in the operating points which often move outside the boundaries. We have defined three boundaries to mimic Rasmussen's limits to test our model:

1. The ***acceptable performance boundary*** is defined as the time patient spent within the ED, measured in minutes. Acceptable performance targets for accident and emergency department laid down by the UK government is 240 minutes (4 hours). In addition, we also measured the total number of patients within the system. This gives an indication of 'bed gridlock' or lack of available treatment rooms to meet the demand.
2. *The* ***economic failure boundary*** is crossed when the hospital uses more than the budgeted funds. Here we use on call doctors to fill in when there is a surge in patient demand. The numbers of maximum allowable on-call doctors are considered 2 for unanticipated situations (this is the marginal boundary). Anything above two on-call doctors per hour is considered economic failure. In order to keep the 'experiments' manageable we have concentrated on only a single type resource, whilst acknowledging that others play an important role.
3. The ***work load boundary*** is defined by utilization of major room, minor room and nurses. Utilization is defined as the effective hours these agents spend with the patients over the total scheduled work hours. In addition we consider the time that a doctor spends in initial consultation with the patient. The nominated time for initial consultation is 10 minutes when the patient queue is at normal level (less than 5). However, a doctor may work faster (spend less time with the patient) to clear the patients through the ED. The effective intended mean-time of consultation that doctors spend with the patient has minimum levels. This is an adaptive behavior of doctor as an individual agent.

Base case simulation and output generation of measures of boundaries.

The numbers of critical agents used within base case are shown in Table 1. The patient arrival pattern for the simulation was generated randomly and the behavior of base-case arrival and the demand pattern is shown in Figure 3

The simulation results from the outcomes presented here are 3 days of results. We simulated the run for 4 days and excluded day one results for initialization transients. Next we present the results of the measures and the boundaries. Figure 4 shows the measures of simulation results and the boundary conditions. Here adequate buffers of resource agents allow the system to cope with fluctuations seen within the demand pattern shown in Figure 3.

Resources	**No of Budgeted Agents (Base Case)**
Doctors	3
Nurses	5
Major Treatment Room	2
Minor Treatment Room	8
Registration Clerk	2
Laboratory Clerk	2
Discharge Clerk	2
Triage Nurse	2
Phlebotomist	2
ECG Technician	2
Laboratory Technician	2

Table 1 – Stable conditions and it operating regions of the resources and it is observed distributions.

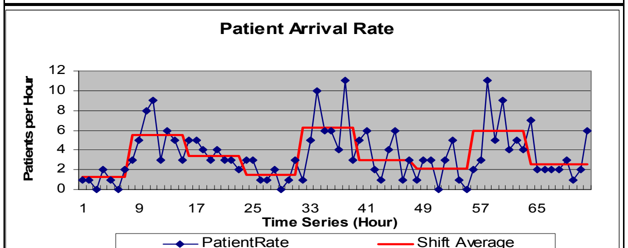

Figure 3: Average number of ED patients arriving in hourly intervals.

The agents, as in real life, change behaviors and rules over time, as they gain experience through encounters with other agents. As agents interact their rules evolve.

Within this ABM we have implemented a simple rule by which doctors change their intended consultation time with the patients based on the ED waiting room queue. This is illustrated in the plot of initial consultation in Figure 4. This shows an increase in waiting room queue due to a short term increase in the number of patients during the hours of 57 to 60.

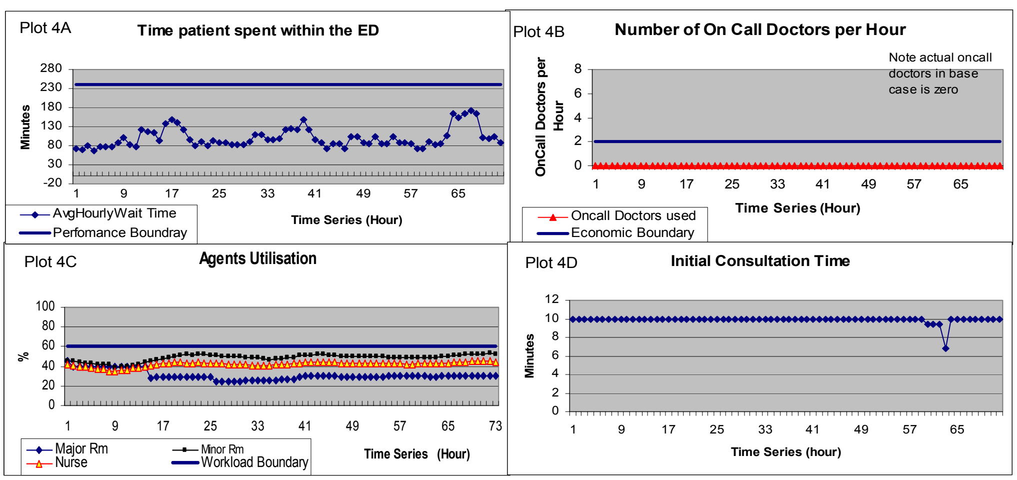

Figure 4: Base-case where it shows a stable 'low risk' system which is operating under a stable condition and would be able to cope with some unanticipated demand increase or resource constraints.

5. Scenario analysis - system dynamics and consequence

This section provides brief results and its implications. First consider the patient arrival rate at ED. The arrival rate depends on various factors, such as weather, age of the population, town center activities (e.g.; traffic accidents), bed occupancy rates in the neighboring hospitals etc. Given a bus accident nearby, there is a short-term increase in patients between 32 – 36 hours as shown in the arrival rate plot in Figure 5. If other agents remained similar to the base-case scenario, the sudden increase in workload pushes the operating region of the safe operating envelope beyond the boundaries of performance and economics. Within this simulation, we constrain all agents to a fixed capacity except for the number of doctors. The simulation increases doctors' capacity to up to nine when the waiting queue increased above 9 by calling in additional doctors to assist in clearing the backlog. Ability to increase the number of doctor agents and doctors who individually work faster was not enough to absorb the effect of the increase in work load depicted by the demand spike. Thus in this scenario, the operating point is pushed more into unacceptable performance boundary with increase in total time patients spent waiting in the ED (over 240 minutes). This in real life situation has the potential to cause major safety concerns.

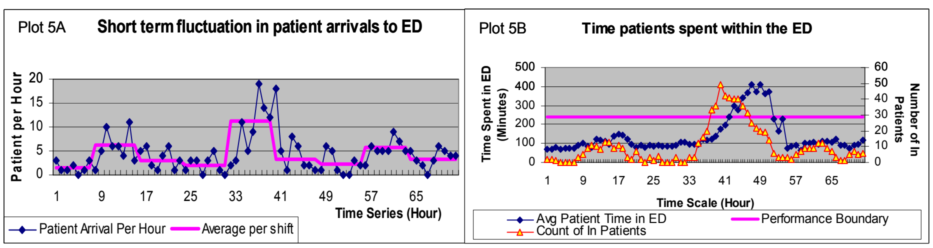

Figure 5 Plots showing the short term fluctuations (increase) in demand pattern relative to base- case. In this scenario a particular spike is notable during 32-36 hrs. One of the out put variables - time-patient spend within the ED is shown to break the performance barrier specified as standard in UK and Australia.

As shown in Figure 4, in the base-case scenario there is no violation of boundary conditions due to ample excess buffer capacities which made the interactions and the dependencies between the agents' couple loosely. In order to test the overall impact of coupling between buffers, we reduced the buffer of the minor room capacity. This situation could be analogous to 'bed block' or 'gridlock 'situations within hospitals where patients still wait in major or minor rooms despite having completed their ED treatment.

Figure 6 illustrates the impact of reducing the minor room capacity from 8 to 3 patients. This will obviously increase the overall utilization of the minor room as shown in plot 6C. As the number of rooms decreases, the rate decreases at which the patients are cleared, increasing the waiting queue whilst also increasing the time that patients spend within the ED. Since the patient queue increases the adaptive behavior of the doctor-agent within the simulation, it increases total number of doctors by drawing on available on-call doctors. Increase in on-call doctors has an impact on stabilizing the system until minor room capacity reduces to 5. Below the minor room capacity of 5,

increasing the number of doctors seem to have no impact on the time a patient spends within the ED and is not able to cope with the inflow of patients as shown by the plot of patients accumulating within the ED. This situation is very similar to work saturation within the hospital system. This leads to ED 'bed block', 'bed crunch' or 'bedlock'. In these situation beds are being occupied by patients who should be discharged or transferred elsewhere, but due to other circumstances are unable to do so.

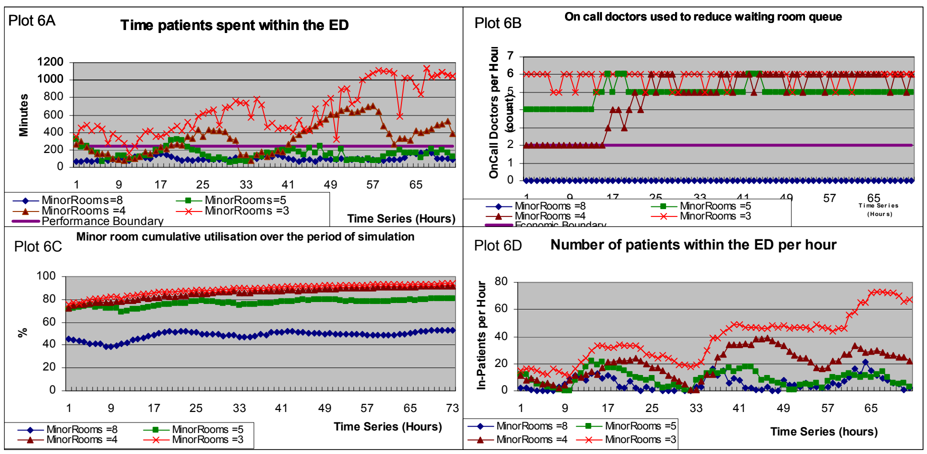

Figure 6: The plot of measures for changing the Minor room capacity from 8 to 3.

6. Conclusions and Future work

The basis for this study is to develop a tool that will be flexible and be able to evolve with the experience of health care systems.

We discussed complex adaptive behavior of a health care system and proposed a framework developed using the example of ED.

We have developed and explored an elementary ABM to show non-linear and adaptive behavior of the health care system's operating parameters and its interdependencies. We argue that ABM has the potential to be a useful tool to study the quality of care and to address the lack of integrative nature of simulation techniques.

The safety dynamics model provided by Cook and Rasmussen is useful for qualitatively visualizing the complex behavior of health care. ABM provides an analytical tool to study the scale and granularity of system behavior, and is able to adapt and learn as the knowledge base and experience evolves. This research is in-progress and we will present more details and field study results in our future publications and presentations. Clearly, agent-based simulation is useful in analyzing complex adaptive behavior of a health care system. With the use of simulation we outlined how Cook and Rasmussen's safety operating envelop can assist in understanding the behavior of a complex system such as ED. Moreover, it highlights implication to economic, acceptable workload and system performance. Unanticipated situations can be dealt with better by modeling and analyzing many other potential scenarios, including those situations involving resource allocations.

This ABM simulation suggests a very feasible modeling framework that can be used to represent the overall health care system and its internal network complexities in a realistic and problem solving fashion.

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