Modeling change in a health system: Implications on patient flows and resource allocations

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Editorial

Linking operations and health services research

Why is the provision of healthcare so hard to improve? Whether we consider Canada,[1] the United Kingdom,[2] Sweden,[3] or the United States,[4] waits, delays, and cancellations negatively impact on patients and their families, teams of care providers, and hospital operations despite the effort and resources directed at solving these problems.[5] At the recent workshop on Modeling Healthcare Systems,[†] it has been argued that at least part of the difficulty is a limited understanding of how changes in organization, management and policy in the health system affect the delivery of healthcare services.

Indeed, the need for new approaches to assess changes before implementing them is well recognized.[6,7] One innovation is the use of computer simulation to identify the likely outcomes of policy and management initiatives.[8] Although simulation of healthcare processes is not new,[9] few health systems have used simulations to re-engineer delivery of health services.[10] There is growing appreciation that the complexity of healthcare processes exceeds the capacity of individual disciplines - health services research or operations research - to substantiate healthcare reform.[11,12]

At the workshop, an international group of scholars has provided sufficient evidence that a new interdisciplinary framework, which links health services research, operations research, and computer sciences, is required. Specifically, it has been argued that the evaluation of policy initiatives should include the simulation of health-system operations.[13] In turn, the methodological rigor of evaluative studies should be applied to the analysis of simulation experiments.[14]

Health services research is the study of the organization, use and outcomes of healthcare delivery. Over the last three decades it has documented wide variations in outcomes of healthcare delivery to the patient population.[15] Yet, health services research has not been sufficient for predicting the impacts of changes in organization and management of surgical care owing it to ethical and methodological constraints for conducting comprehensive research on management alternatives in the hospital setting. As such, the link between organization of hospital services and patient outcomes of care delivery is rarely addressed explicitly or tested empirically.[16]

Computer simulation is an operations research technique to evaluate a system's performance.[17] The underlying premise is that a collective experience of simulated paths through the system is the result of the system's operations.[18] Modeling patient flow is considered a powerful approach to assessing the likely response of a health system to changes in organization, management and policy.[19] Applications of the simulation approach include evaluation policies for hospital admission,[20] scheduling appointments,[21] capacity planning,[22] bed planning,[23] patient flow,[24] and wait-list management.[25]

Simulations facilitate reaching consensus on resource allocation by providing estimates under different scenarios considered by decision-makers[26] and boost the credibility of a request for healthcare resources by showing event chronology, volume and mix.[25] It is also recognized that the uncertainties and complexity of healthcare delivery exceed the capacity of the current state of analytic modeling to predict the consequences of individual actions taken by specialists, hospital managers, or patients.[20,27] Most modeling efforts are generally intended to capture limited phenomena, or a small part of a larger process. Some argue that understanding patient flow requires looking at the entire peri-operative process, rather than individual activities.[5]

Applying simulation to healthcare has given birth to a variety of approaches to constructing modeling instruments.[28] **System dynamics** approach represents aggregated patient flow as continuous-time changes in the population of system states. System dynamics models have been used in simulations of primary, secondary and community healthcare.[29] The models were constructed for both an individual emergency department,[30] and the entire system of emergency care in a region.[31] Although system dynamics methods are used for understanding the structural sources of different behaviour modes, the utility of the approach for studying changes in policy and organization is not known.

Markov models are extensively used to evaluate healthcare policies.[32] The aggregated flow of patients through a system is represented by a finite set of states

† The workshop was funded through the Peter Wall Institute for Advanced Studies Exploratory Workshop Program and the Canadian Institutes for Health Research Symposium Grant, www.mhcs.pwias.ubc.ca

and transition probabilities. A limitation of using Markov models for complex systems is that it is not possible to describe interaction between concurrent processes.

In the ***discrete-event simulation*** approach, the functioning of a system is modelled as a finite-state machine with transitions occurring upon some events.[33] It has been argued that discrete-event simulation is especially appropriate in healthcare, where patients are subject to multiple concurrent processes and placed in multiple queues.[28] Discrete-event simulations have been used to study outpatient clinics,[34] emergency admissions,[35] peri-operative process,[36] and treatment of coronary artery disease.[37] By simulating processes that advance individuals through a system, these models are more understandable and more closely resemble reality than Markov models, in which transition probabilities are applied equally to all members of a pre-defined cohort.

In the ***agent-based approach***, the system's functioning is modeled by the behavioural specification of each agent (patient, caregiver, manager, organization) and rules of interaction between agents. It has been argued that the agent-based approach allows realistic representation of complex organizations and concurrent behaviour patterns.[38] The approach has been applied to performance evaluation in manufacturing[39] and clinic appointments.[40] Agent-based reasoning was used for scheduling, information search, and distributed medical diagnostic facilities.[41] However, its utility for patient flow modeling is not well understood.

There is an increasing number of applications of ***visual formalisms*** to modeling queuing systems for performance evaluation.[42] For example, Statecharts uses notions of subordination between states, parallel states, and event broadcasting for describing reactive event-driven systems.[43] In addition to being a specification language, Statecharts is executable and used as a simulation engine.

Despite a variety of approaches, little research is available on the appropriateness of modeling techniques when the goal is to assess the impact of changes in organization, management and policy on outcomes of delivering health care to the patient population. The purpose of the workshop was to bring together researchers from different disciplines to jointly work toward assessing the research possibilities in the area of modeling healthcare systems and to develop a research agenda. This issue of CIM publishes the extended version of workshop talks presented by scholars, health policy and decision makers.

References

1 Commission on the future of health care in Canada. Improving access, ensuring quality. In: Romanow R, Building on values: the future of health care. Saskatoon: Commission on the Future of Health Care; 2002.

2 Enthoven AC. A promising start, but fundamental reform is needed. BMJ 2000; 320:1329-31.

3 Hanning M, Spangberg UW. Maximum waiting time - a threat to clinical freedom? Implementation of a policy to reduce waiting times. Health Policy 2000; 52:15-32.

4 Committee on Quality of Health Care in America. Crossing the Quality Chasm: A New Health System for the 21st Century. Washington, DC, USA: National Academy Press; 2001.

5 Haraden C, Resar R. Patient flow in hospitals: understanding and controlling it better. Front Health Serv Manage 2004; 20:3-15.

6 Walshe K, Rundall T. Evidence-based management: from theory to practice in health care. Milbank Q 2001; 79(3):429-42V.

7 Watt S, Sword W, Krueger P. Implementation of a health care policy: an analysis of barriers and facilitators to practice change. BMC Health Serv Res 2005; 5:53.

8 Harper PR. A framework for operational modelling of hospital resources. Health Care Manag Sci 2002; 5(3):165-173.

9 Bailey NTJ. A study of queues and appointment systems in hospital out-patient departments, with special reference to waiting-times. Journal of the Royal Statistical Society (Series B) 1952; 41:185-198.

10 Young T. An Agenda for Healthcare and Information Simulation. Health Care Manag Sci 2005; 8(3):189-196.

11 Berwick DM. The John Eisenberg lecture: health services research as a citizen in improvement. Health Serv Res 2005; 40(2):317-336.

12 Sheils J. Estimating the impacts of health care reform. Milbank Q 2003; 81(1):151-154.

13 Butler TW, Reeves GR, Karwan KR, Sweigart JR. Assessing the impact of patient care policies using simulation analysis. J Soc Health Syst 1992; 3(3):38-53.

14 Ukoumunne OC, Gulliford MC, Chinn S, Sterne JA, Burney PG, Donner A. Methods in health service research. Evaluation of health interventions at area and organisation level. BMJ 1999; 319(7206):376-379.

15 Buhaug H. Long waiting lists in hospitals. BMJ 2002; 324(7332):252-253.

16 Aiken LH, Sochalski J, Lake ET. Studying outcomes of organizational change in health services. Med Care 1997; 35(11 Suppl):NS6-18.

17 Jun JB, Jacobson SH, Swisher JR. Application of discrete-event simulation in health care clinics: a survey.

Journal of the Operational Research Society 1999; 50(2):109-123.
18 Mahachek AR. An introduction to patient flow simulation for health-care managers. J Soc Health Syst 1992; 3(3):73-81.
19 Davies HTO, Davies R. Simulating health systems: modelling problems and software solutions. Eur J Oper Res 1995; 87:35-44.
20 Gallivan S, Utley M, Treasure T, Valencia O. Booked inpatient admissions and hospital capacity: mathematical modelling study. British Medical Journal 2002; 324(7332):280-282.
21 Worthington D, Brahimi M. Improving out-patient appointment systems. Int J Health Care Qual Assur 1993; 6(1):18-23.
22 Ridge JC, Jones SK, Nielsen MS, Shahani AK. Capacity planning for intensive care units. Eur J Operational Research 1998; 105:346-355.
23 Millard PH, Mackay M, Vasilakis C, Christodoulou G. Measuring and modelling surgical bed usage. Ann R Coll Surg Engl 2000; 82:75-82.
24 Rotondi AJ, Brindis C, Cantees KK, DeRiso BM, Ilkin HM, Palmer JS et al. Benchmarking the perioperative process. I. Patient routing systems: a method for continual improvement of patient flow and resource utilization. J Clin Anesth 1997; 9(2):159-169.
25 Benneyan JC. An introduction to using computer simulation in healthcare: patient wait case study. J Soc Health Syst 1997; 5(3):1-15.
26 Everett JE. A decision support simulation model for the management of an elective surgery waiting system. Health Care Manag Sci 2002; 5(2):89-95.
27 Cayirli T, Veral E. Outpatient scheduling in health care: a review of literature. Production and Operations Management 2003; 12(4):519-549.
28 Fone D, Hollinghurst S, Temple M, Round A, Lester N, Weightman A et al. Systematic review of the use and value of computer simulation modelling in population health and health care delivery. J Public Health Med 2003; 25(4):325-335.
29 Wolstenholme EF. A patient flow perspective of U.K. health services: exploring the case for new "intermediate care" initiatives. System Dynamics Review 1999; 15(3):253-271.
30 Lattimer V, Brailsford S, Turnbull J, Tarnaras P, Smith H, George S et al. Reviewing emergency care systems I: insights from system dynamics modelling. Emergency Medicine Journal 2004; 21(6):685-691.
31 Brailsford S, Lattimer VA, Tarnaras P, Turnbull JC. Emergency and on-demand health care: modelling a large complex system. Journal of Operational Research Society 2004; 55(1):34-42.
32 Karnon J. Alternative decision modelling techniques for the evaluation of health care technologies: Markov processes versus discrete event simulation. Health Econ 2003; 12(10):837-848.
33 Banks J, Carson JSI, Nelson BL. Discrete-event system simulation. 3rd ed. New Jersey: Prentice-Hall; 2001.
34 Harper PR, Gamlin HM. Reduced outpatient waiting times with improved appointment scheduling: a simulation modelling approach. OR Spectrum 2003; 25(2):207-222.
35 Bagust A, Place M, Posnett JW. Dynamics of bed use in accommodating emergency admissions: stochastic simulation model. British Medical Journal 1999; 319(7203):155-158.
36 Stahl JE, Rattner D, Wiklund R, Lester J, Beinfeld M, Gazelle GS. Reorganizing the system of care surrounding laparoscopic surgery: a cost-effectiveness analysis using discrete-event simulation. Med Decis Making 2004; 24(5):461-471.
37 Cooper K, Davies R, Roderick P, Chase D, Raftery J. The development of a simulation model of the treatment of coronary heart disease. Health Care Manag Sci 2002; 5(4):259-267.
38 Shen W, Norrie DH. Agent-based systems for intelligent manufacturing: a state-of-the-art survey. Knowledge and Information Systems 1999; 1(2):129-156.
39 Sadeh NM, Hildum DW, Kjenstad D. Agent-based e-supply chain decision support. Journal of Organizational Computing and Electronic Commerce 2003; 13(3-4):225-241.
40 Charfeddine M, Montreuil B. Conception d'un simulateur de services de santé centrés clients. 6th Congrès International de Génie Industrie, Besançon, France; 05 Jul 11; Honolulu, Hawaii USA. Institut de productique, 2005
41 Kirn S, Herrler R, Heine C, Krempels KH. Agent.Hospital - agent based open framework for clinical applications. 12th IEEE International Workshop on Enabling Technologies: Infrastructure for Collaborative Enterprises. IEEE Computer Society, 2003
42 Francês C, Oliveira E, Costa J, Santana M, Santana R, Bruschi S et al. Performance evaluation based on system modeling using Statecharts extensions. Simulation Modelling Practice and Theory 2005; 13(7):584-618.
43 Harel D, Politi M. Modeling Reactive Systems with Statecharts: The STATEMATE Approach. McGraw-Hill; 1998.

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ORIGINAL ARTICLE

Shooting arrows in the dark: The policies and practices of waitlist management in Canada

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Abstract

Wait times for medical procedures in Canada are universally thought to be too long, particularly for elective procedures. In this paper we point out the conceptual and practical difficulties surrounding wait list management in Canada. We suggest that while waits need to exist as a distributive allocation policy, the data to make informed decisions about wait times and their impact on patient care is absent. We also show that current waitlist initiatives lack an underlying conceptual model of why waits occur. The paper concludes with a discussion of why operational research (OR) models are not in greater use for wait list management and suggest a program of research to improve knowledge uptake for OR models.

Introduction

In Canada, as in much of the industrialized world, there is a great deal of interest from the public, governments, and policy analysts around the issue of waits for medically necessary treatments. In 2005, the federal government, in partnership with the provincial ministries of health announced a $41 billion initiative to reduce waits, specifically targeted at orthopaedics, cataract surgery, cancer, cardiac care, and diagnostic imaging.[1] Concern over wait times for health care is not a new phenomenon; specific instances have been noted in the academic literature for over 15 yr: reports in the popular press are legion. A recent decision by the Supreme Court of Canada (Chaoulli v. Québec) which paves the way for the buying and selling of private insurance for medically necessary services, places further emphasis on wait times in Canada.[2]

It is clear that as a country we are now, and for the foreseeable future will be, spending a great deal of money to ameliorate wait times for medical services. It may well be worthwhile asking ourselves at this juncture, what we really know about demand for medical services, patient wait times, how to measure and monitor waits, and what to do to address wait time issues when they are identified. Curiously, although wait times are universally acknowledged to exist and to be too long, there is relatively little we can say about wait times with any certainty.[3,4] Furthermore, techniques for managing the health care system to address excessive waits are largely absent from the policy arena in this country.

To quote MacDonald, Shortt, Sanmartin, Barer, Lewis, and Sheps.[3]

> *With rare exceptions, waiting lists in Canada, as in most countries are non-standardized, capriciously organized, poorly monitored, and (according to most informed observers) in grave need of retooling.*
>
> *As such, most of those currently in use are at best misleading sources of data on access to care, and at worst, instruments of misinformation, propaganda, and general mischief.*

Is Waiting for Service Always Bad?

Despite this popular tendency to view all waits as bad, there is a substantial body of literature in the policy domain to indicate that waiting for services has some benefits, at least from a distributive point of view.[5]

Health care is a social good; unfortunately it is also a scarce resource, either because of natural shortage or through allocative decisions. Since additional health care benefits (at least infinitesimally) the individual receiving it, demand for health care is infinite, while supply is finite. Thus, regardless of the system in question some form of rationing is necessary.[5]

It is possible to ration health care strictly on the basis of price and, by extension the individual's ability to pay, but price rationing has several flaws. The chief complaint associated with rationing by price is that it creates a potentially absurd distribution of a scarce resource; those most able to pay may not be the most in need.

Queuing, by contrast, represents a form of non-price rationing. Since time is thought to be more equitably distributed than money, queuing is thought to be a more equitable mechanism than rationing by price.[5] Furthermore, queuing, particularly first-come, first-served, is broadly understood within society and is seen as being "fair".

Queues, however, are not without their drawbacks. Queues tend to mask mismatches between supply and demand. Thus, situations can arise where supply greatly outstrips demand, but because a queue is seen as normal, society is slow to make changes to restore equilibrium. First-come, first-served policies may, like price rationing, result in absurd allocations: the people receive services not because they are most in need, but because they happen to be at the front of the line.[5]

To counter the issue of absurd allocation, many health care queues are prioritized; patients are stratified by need and the more deserving go to the head of the line. Unfortunately, stratification can be capricious, particularly if the prioritization decision is shared by several individuals; what one decision may think deserving, another may consider frivolous. Finally, it has been well documented that prioritized queuing systems can be gamed; there is an abundant literature in Canada that indicates the wealthy are able to access health care to a much greater extent than the poor.[6]

Wait List Management in Canada

Some form of health care rationing is always necessary. Canada has a legacy of using queues as a distributive policy. (Canada is not unique in this aspect; the OECD notes that queues exist in many countries.[7]) Given the legacy of queuing as a distributive technique, most strategies for wait list management focus on methods to improve the effectiveness of stratified queuing mechanisms. The specific mechanism for achieving this can be broadly separated into three domains: patient prioritization; wait list estimation; and patient registries.

Prioritization Schemes

Perhaps the most visible patient prioritization project is the Western Canada Wait List (WCWL) project.[8] Five different tools were developed as part of this project for different clinical conditions. The tools employ an additive point-count measure, based on a variety of clinical dimensions and were evaluated by comparing score totals for a set of case studies against a visual analogue scale (VAS). Regression analysis of the point scores against expert use of the VAS suggests mixed results, with correlation coefficients ranging from 0.36 to 0.62. Thus, the ability of prioritization tools to remove subjectivity remains an open question. More significantly for the Canadian health care system, no attempt has been made to use prioritization tools to establish minimum thresholds for need.

Wait List Estimation

Despite the fact that waits are almost universally thought to be too long, there are very few regions in Canada for which definitive statements can be made about the true nature of the queues encountered by patients.

Historically, surgeons in Canada have maintained their own individual wait list records, usually in paper format, and without any common data standards or definitions. The lack of a single repository of patient information significantly impacts the quality of wait time data available in Canada. Methods for estimating patient wait times by surveying specialists are known to be unreliable and subject to bias or manipulation. (A 2005 audit of 68,000 patients on waiting lists in BC discovered that roughly 8,000 patients were either redundant, double counted, dead, or no longer in need of surgery.[9]) Nevertheless, survey methods form the basis for a great deal of decision making in Canada. Most Canadian provinces including are now actively gathering wait time data from specialists and posting it online.[9] It is believed by many that if wait time information is broadly known, patients will naturally redistribute themselves to institutions with smaller lines, though there has been no formal testing of this hypothesis.

Registries
A number of jurisdictions have begun to build or install wait list registries. The Capital District Health Authority in Halifax, Nova Scotia has recently purchased a Canadian made computerized (Access Rx) wait list management tool. The software is designed to be a central repository for all patients awaiting surgery at a CDHA institution.

Registry methods have a number of advantages over survey methods for estimating queue size: the data is more meaningful, since common definitions and data standards are in place. However, there are substantial capital and operating costs associated with registry methods. Since the systems are local and rely upon distributed input, redundancy, double counting, and patient attrition remain issues to be addressed.

Wait Time Crisis: Your Money or Your Life
Wait time crisis tend to follow a relatively predictable trajectory.[10] In a typical scenario, attention is drawn by a prominent clinician to a wait time issue in his or her clinical practice. There is often an indication that the waits causing suffering or death amongst patients. The issue is taken up by the media. Attempts at determining the size and scope of the problem are frustrated by a lack of objective wait time data; anecdotal information is used for decision making. The crisis grows until abated by an infusion of resources by government. The size of the health care system increases and the problem goes away, at least for a while. Increasing the resources available in the system has the immediate effect of increasing capacity and decreasing wait. However, as wait decreases, so also does the threshold for need. Over time the latent demand arising from the lower threshold increases traffic intensity and the system eventually returns to its congested state.[11]

Latent demand creates a practical problem for health care funders. A number of studies suggest that increased spending does not correlate to decreased wait times for patients. Provincial ministries of health are therefore reluctant to provide funding holus bolus without some indication that that additional funding will secure real reductions in wait times.

Health care and Operational Research
Operational Research (OR) techniques such as queuing theory and simulation would seem to offer an ideal framework for informing wait list decisions. Indeed, there is a plethora of OR studies in health care in the literature, including a number of Canadian studies. Curiously, however, operational research models have been largely absent from the current debate about wait times in Canada.

A number of OR researchers have commented on the difficulty in applying quantitative models in health care. Some note the dual management structure in place in health care. Others point to a difference in training and inclination between OR researchers and policy makers. Carter and Blake[12], describing applications within the Canadian system note that OR models are time consuming and expensive to build. Specialist skills needed to build and develop models in existing simulation environments makes OR models expensive, while the time required to obtain and analyze sufficient data to build, test, and validate a simulation model is posited as being the limiting step in most studies. For example, in the area of wait list, accurate information about true demand for service is notoriously difficult to obtain. Finally, while most hospitals have care processes that are similar, there is enough variation in clinical and administrative practice from institution to institution to make it difficult to create a generic simulation model of a hospital or health care system.

Shedding Light on the Problem: How Can We Increase the Diffusion of OR Models
Operational Research techniques do offer a useful framework for informing wait list decisions and should be an integral component of wait list management in Canada. However, to increase the diffusion of OR models in health care, research is required to extend the modelling environment for health care operations and to build infrastructure to support evidence based decisions on wait lists and their management.

Infrastructure
Like all decision makers in health care, OR modellers are effected considerably by the lack of universal wait list data. As a community of researchers, operational researchers must support efforts to collect wait time information in standard registries, using standard definitions and data collection procedures. These efforts will ultimately yield data that will provide a more comprehensive measure of demand. OR researchers must also support infrastructure developments that will provide greater process flow data, for example through the in-house electronic medical records. Finally, there is a need to support the extension of data collection throughout a patient's entire cycle of care (the electronic health record) so that the outcomes of care can be determined.

An Agenda for Operational Research

To ensure that wait list issues are addressed in a timely and cost effective manner, the OR community must make efforts to make modelling faster, cheaper, and more generalisable. As a first step, effort should be expended to create a taxonomy to describe, within a single unified body of knowledge patients, flows, resources, and institutional management parameters. A valid comprehensive taxonomy (for example like Kendall-Lee notation in queuing theory) would provide a framework for conceptualizing instances of patient care, would speed process modelling, and would make models more generalisable since results would apply to a class of institutions, rather than just a single hospital or system.

As a community it is also important that the OR community develop a modelling environment suitable for simulating patient flow and addressing wait list issues. The environment is not simply a re-packaging of existing manufacturing simulation widgets into hospital widgets (i.e a machine as a bed) , but rather the creation of a set of elemental modelling constructs, based on a comprehensive taxonomy with defined data elements and standards, that can be used to build robust, reliable, and reusable simulation models. Once such an environment is in place, the OR community can conduct elemental research into the factors that affect patient flow. This will help identify key control parameters and uncover correlation between factors and thus establish what factors, in what circumstances, are key to effectively managing and controlling wait time.

Finally, the OR community needs to ensure that the newly defined modelling framework is embedded in a user environment that is not only simple to use, but which supports valid modelling, assists users in verification and validation, and has embedded tools to support statistical output.

If the OR community can take these steps, it would enable the migration of modelling activities from the research domain into ordinary planning activities. If the community can increasing the complement of modellers in this country, through the development of a robust, easy to use simulation environment, there is indeed hope that evidence based decisions about wait lists and wait list management can be made and that the extra resources promised for Canada's health care system can be used efficiently and effectively.

References

1. Dosanjh U. Statement from Health Minister Ujjal Dosanjh on the Wait Time Alliance's interim report`. 2005; Available at: http://www.hc-sc.gc.ca/ahc-asc/minist/health-sante/messages/2005_04_04_e.html. Accessed 9/28, 2005.
2. McFarlane L. Supreme Court slaps for-sale sign on medicare. CMAJ 2005;173:269-70.
3. MacDonald PW, Shortt S, Sanmartin C, et al. Waiting lists and waiting times for health care in Canada: More management!! More money?? Ottawa: Health Canada; 1998.
4. Lewis S, Barer ML, Sanmartin C et al. Ending waiting-list mismanagement: principles and practice. CMAJ 2000;162:1297-300.
5. Calabresi G, Bobbitt P. Tragic choices. 1st ed. New York: Norton; 1978.
6. Shortt SED, Shaw RA. Equity in Canadian health care: Does socioeconomic status affect waiting times for elective surgery? CMAJ 2003;168:413-6.
7. Hurst J, Siciliani L. Tackling Excessive Waiting Times for Elective Surgery: A Comparision of Policies in Twelve OECD Countries. Paris: OECD; 2003.
8. Noseworthy TW, McGurran JJ, Hadorn DC. Waiting for scheduled services in Canada: development of priority-setting scoring systems. J Eval Clin Prac2003;9:23-31.
9. Median Wait Times and Wait Lists. 2005; Available at: http://www.healthservices.gov.bc.ca/cpa/mediasite/waittime/median.html. Accessed 09/28, 2005.
10. Naylor CD. A different view of queues in Ontario. Health Affairs 1991;10:110-28.
11. Esmail N. Spend and Wait. Fraser Forum 2003 March:25-26.
12. Carter M, Blake J. Using simulation in an acute care hospital: Easier said than done. In: Brandeau ML, Sainfort F, Pierskalla WP, editors. Boston: Kluwer Academic Press; 2005. p. 191-215.

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ORIGINAL ARTICLE

Overcoming the barriers to implementation of operations research simulation models in healthcare

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Summary

Since the 1960s, Operations Research models have been applied to a range of healthcare problems. Despite the proliferation of papers in the academic literature, and individual anecdotal success stories, there are still major issues around getting OR models widely accepted and used as part of mainstream decision-making by clinicians, health managers and policy-makers. In this paper, focussing on simulation models, we discuss some of the possible reasons for this, briefly describe one successful implementation and suggest some potential ways forward.

Introduction

Operations Research (OR) has existed as a scientific discipline for around 60 years and has been applied to healthcare for over 40 years. The UK OR Society and the National Health Service (NHS) held a joint Colloquium on hospital appointment systems in 1962.[1] Since then OR models have been successfully used to assist clinical decision-making, facility planning, resource allocation, evaluation of treatments, and organisational redesign. One of the most commonly used approaches is computer simulation, widely regarded as the technique of choice in healthcare because of its power and flexibility. A recent electronic literature search, using the Web of Knowledge[2] and the keywords "health" and "simulation" found 3,426 references. The keywords "simulation" and "hospital" gave 1,041 hits, and "simulation" and "emergency department" gave 1,008 hits. A review paper of simulation models for outpatient clinics[3] contained 117 references.

Despite this proliferation of academic publications, and unlike manufacturing industry where a similar literature exists, there has been no widespread take-up of simulation by the healthcare industry. This is true even in the UK, where the Department of Health has an Operational Research group[4] and one might expect OR models to be institutionalized and widely used within the NHS. This is certainly not the case. The picture is more of countless "consultancy" projects carried out by academics, published in academic journals, but not widely adopted by other health providers.

The problems of getting models implemented are not new. A 1977 paper, tellingly entitled "Why won't anyone believe us?"[5] describes the difficulties of using simulation models to influence policy-makers. A 1981 survey of simulation projects in healthcare[6] found 200 papers, only 16 of which reported successful implementation. Common factors in these 16 included: at least one author who worked at the institution concerned, timeliness (a high priority problem), external funding, and a detailed description of data collection. A systematic review in 2003[7] of healthcare simulation models found 182 papers published between 1980 and 1999, yet very few examples of implementation. The authors say

> *"… we were unable to reach any conclusions on the value of modelling in health care because the evidence of implementation was so scant."* [7], p. 333

A successful implementation - the Nottingham emergency care project

Nottingham is a city of 650,000 inhabitants in the East Midlands of England. In 2002 the local health authority set up a Steering Group to address the problem of increasing demand for unscheduled care. In particular, a steep rise in emergency hospital admissions over the past three years had led to a similar increase in cancelled elective surgeries, and frequent "red alerts" when the hospitals were closed to all except emergency admissions. The Steering Group consisted of representatives from all providers of emergency and unscheduled care: the Ambulance Service, the hospitals, in-hours and out-of-hours GP services, Social Services, Mental Health Services, NHS Direct (a 24/7 telephone service), the Walk-in Centre (a nurse-run no-appointment service), Community Health, patient representatives, and a research team from the University of Southampton led by Dr Val Lattimer from the School of Nursing and Midwifery.

The research had a number of strands, of which OR simulation modelling was just one. System Dynamics was selected as the modelling tool because of its strategic perspective and its ability to model feedback effects in large, complex systems. System Dynamics models are fast to run, which was a big advantage as it allowed "what-if" experimentation at Steering Group meetings. The model has been described in detail elsewhere.[8,9] A process of in-depth interviews and discussions resulted in a patient flow map and influence diagrams which were then developed into a quantitative model using the software Stella.[10] The Stella model enabled the Steering Group to experiment with different scenarios and see immediately the impact of making changes.

The findings were presented to the Steering Group in May 2002, and a "Stakeholder Day" held in June at which focus groups discussed four key areas identified for change. A Local Services Framework for emergency care was developed and the recommendations implemented early in 2003. Currently, the UK Department of Health is considering extending the use of the model to other areas.

Many factors contributed to the success of this project, several in agreement with.[6] Firstly, the impetus for the project came from the client - it addressed an urgent high-profile problem in Nottingham. A charismatic and enthusiastic local sponsor chaired the Steering Group, and there was a spirit of remarkable goodwill and cooperation among its members. The research team itself was multi-disciplinary; health service researchers and health economists worked alongside the OR team. Data collection was given high priority. The project was also high on the national political agenda - the right model at the right time. The model was developed throughout with involvement of the Steering Group. A key factor was the simplicity and interactive nature of the model. Crucially, money was available to develop the model in the first place and to implement the recommendations.

Barriers to implementation

Simulation has been accepted as a standard tool by manufacturing industry for decades, and the benefits which have accrued from the use of simulation are undisputed. Billions of dollars of savings have been made by the use of models which allow risk-free experimentation with production layouts, machine scheduling rules and so on. Few manufacturing companies would dream of building a new production line without first evaluating the available options through a computer simulation. So why is this not the case in healthcare? Is healthcare intrinsically or structurally different from manufacturing, making the application of simulation more difficult? If so, what can we do about it? Harper and Pitt[11] describe some of the problems facing the would-be healthcare modeller. Below we outline a few of the key issues.

Culture

Firstly, the healthcare industry is characterised by constant change, upheaval and stress. The traditional clinical hierarchy of doctors and nurses is being replaced by a new management hierarchy, driven in the UK at least by Government-imposed league tables and performance targets. Many healthcare workers are resistant to yet more change: as they struggle just to cope with each day's workload. There is psychological resistance to methods adopted from manufacturing industry, and a feeling that such models are trying to reduce human beings to widgets in a production line and thus are doomed to failure. Moreover, in the UK, the NHS has a poor track record with IT projects, one of the most famous examples being the London Ambulance Service Computer Automated Dispatch system in the early 1990s.[12]

Cost

Cost is a major issue. Most simulation software is costly, and modelling and statistical expertise is very expensive. Despite the vast amount of data collected routinely in hospitals, it is rarely in a form suitable for modelling, so further money has to be spent on data cleaning and analysis. Simulation projects are therefore a major investment for the client, and understandably hospitals are unwilling to share their models. In the UK this is aggravated by the artificial competition resulting from the league table system, and in other countries such as Canada it is aggravated by genuine financial competition between hospitals.

Data

All models need data, and healthcare data are notoriously of poor quality. Many hospitals still use legacy and incompatible computer systems at best or paper-based systems at worst. With time, things are slowly changing: more robust, user-friendly and sophisticated IT systems are gradually being introduced and hospital staff are becoming more computer-literate. Academic research in areas such as data-mining has provided better tools for handling and manipulating large datasets. Nevertheless some issues, such as the legal status of certain patient documentation, have yet to be satisfactorily resolved.

Perverse incentives

The high prices charged by business consultancies has meant that much healthcare modelling work is carried out as research/consultancy projects by academics. However, academics and their clients work to different agendas. Academics need to publish in peer-reviewed journals and must thus demonstrate theoretical or methodological advances. This leads to complex, sophisticated models, in stark contrast with the objective of the end-user: a simple, easy-to-use model. This conflict has been aggravated by research funding allocation mechanisms such as the UK government's Research Assessment Exercise.

Generic or specific

All modellers stress the importance of involving the client/end user at every stage of model development, as being the only way to secure buy-in. There is clear evidence for the "Not Invented Here" syndrome: "This model would not work for our hospital because we have a totally different process for dealing with hip fractures in the elderly" and so on. This suggests generic models for healthcare may not be feasible. However the question remains: do we really need 1,008 different simulation models of Emergency Departments?

Lessons from industry

One clear advantage that manufacturing industry has over healthcare is that the education and training of engineers includes simulation and computer modelling, so there is no psychological barrier to be overcome. The value of simulation is self-evident and so the necessary money will be found. The costs are considerably reduced due to a further advantage of manufacturing: the software tools (for example, Witness,[13] ProModel,[14] and Simul8[15]) are generic and can be applied in virtually any manufacturing system. The basic components - workstations, conveyors, resources, buffers and so forth - are common to all production systems. The ability to link these in a flexible way to model a particular system is key. There have been some attempts to do this in healthcare (e.g. the software MedModel[16]) but to date these have only met with limited success. The developers of MedModel clearly believe there is an intrinsic difference between healthcare and manufacturing industry, and argue that

> *"The problem of finding such a tool actually extends beyond simulation itself since simulation long ago proved its value to the manufacturing sector. However, pure manufacturing is anything but an accurate reflection of what happens in a healthcare setting."* [17], p. 233

Challenges for academia and for practitioners

One of the toughest challenges for academia will be finding a way to deal with the perverse incentives problem. We have to play the game: we cannot change the system overnight. Moreover, there will always be a need for original, ground-breaking theoretical research for which no immediate application is obvious. However, since its inception, OR has been a discipline focussed on solving real-world problems. Addressing the problems of real hospitals and real patients is paramount.

Modellers need to develop new approaches to tackle the tough cultural problems inherent in the healthcare system. A key step is finding the right person who can act as an enthusiastic and powerful sponsor within the organisation. Operations Researchers also need to work alongside other disciplines such as health services research and health economics in order to exploit the synergies between them.

There are further research challenges in developing truly generic models acceptable to all users, balancing user-friendliness with scientific rigour and validity, and in identifying the right "building blocks" or basic components of all patient flow systems, so that users can easily modify existing models and tailor them to their own hospital, in order to achieve the necessary sense of ownership.

Similar challenges face the healthcare providers: through pooling resources and working together (with universities and software vendors, but most of all, each other), overcoming the cultural issues and resistance to change, and implementing robust, practical data collection systems, the benefits long achieved in manufacturing industry can begin to be achieved in health.

A new initiative in the UK aims to meet all these challenges. The Network for Modelling and Simulation in Health, MASHnet,[18] has recently been funded by the UK's Engineering and Physical Sciences Research Council to bring together the three communities: academia, healthcare providers and industry (software vendors and consultants). The time is right for collaboration and there is really exciting research to be done. Academics and practitioners should be ready to work together on real-world problems which have the potential to make huge improvements to healthcare systems worldwide.

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References

1. Jackson, RRP. Appointment systems in hospitals and general practice. Opl Res Quart 1964; 15: 219-37.
2. http://wos.mimas.ac.uk/, accessed September 15, 2005.
3. Jun, JB, Jacobson, SH and Swisher, JR. Application of discrete-event simulation in health care clinics: A Survey. J Opl Res Soc 1999; 50:109-23.
4. http://www.operational-research.gov.uk/public/dh.html, accessed September 15, 2005
5. Watt KEF. 1977. Why won't anyone believe us? Simulation 28: 1-3.
6. Wilson, JCT. Implementation of computer-simulation projects in healthcare. J Opl Res Soc 1981; 32: 825-32.
7. Fone D, Hollinghurst S, Temple M et al. Systematic review of the use and value of computer simulation modelling in population health and health care delivery. J Publ Health Med 2003; 25: 325-35.
8. Brailsford, SC, Lattimer, VA, Tarnaras P, Turnbull, JC. Emergency and on-demand health care: modelling a large complex system. J Opl Res Soc 2004; 55: 34-42.
9. Lattimer, VA, Brailsford, SC et al., Reviewing emergency care systems I: insights from system dynamics modelling. Emerg Med J 2004; 21: 685-91.
10. STELLA, High Performance Systems, 45 Lyme Road Suite 300, Hanover NH 03755, USA.
11. Harper, PR, Pitt, MA. On the challenges of healthcare modelling and a proposed project life-cycle for successful implementation. J Opl Res Soc 2004; 55: 657-61.
12. Flowers, S., Software Failure: Management Failure. Wiley, Chichester, UK, 1996.
13. http://www.lanner.com/home/the_value_of_knowing.php accessed September 19, 2005.
14. http://www.promodel.com/ accessed September 19, 2005.
15. http://www.simul8.com/ accessed September 19, 2005.
16. http://www.promodel.com/products/medmodel/ accessed September 19, 2005.
17. Harrell, CR and Lange, V. Healthcare simulation modelling and optimization using MedModel. Proceedings of the 2001 Winter Simulation Conference, 2002, ed. Peters, BA, Smith, JS, Medeiros, DJ and Rohrer, MW. 233-238.
18. http://www.pms.ac.uk/mashnet/ accessed September 19, 2005.

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ORIGINAL ARTICLE

Bottleneck analysis of emergency cardiac in-patient flow in a university setting: an application of queueing theory

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Capacity decisions in Dutch hospitals are generally made without the help of OR model-based analyses. For several years hospital managers have been under pressure to reduce bed capacity and increase occupancy rates in the name of operational efficiency. This strategy is questionable. Variability in arrival process and length of stay (LOS) can have a major impact on hospital operation and capacity requirements. If this variability is neglected during modeling an unrealistic and static representation of reality will emerge. Such a model, based on average numbers, is not capable of describing the complexity and dynamics of in-patient flow. Too often, management does not consider the total care chain from admission to discharge, but mainly focuses on the performance of individual units. Not surprisingly, this has often resulted in diminished patient access without any significant reduction in costs.

Relevance
The number of refused admission at the first cardiac aid is significant and, consequently, numerous patients are turned away to other surrounding hospitals. In the last three years approximately one out of every eight arriving patients was refused admission. This means that, roughly, one patient per day is turned away. This is unacceptable and puts great pressure on the required service level. More and more hospitals have to account for the quality of care that they deliver. An admission guarantee for all patients entering the emergency department is one of the main goals of the hospital. In the case of a heart attack, the sooner the patient reaches the emergency room, the better is his/her chance of not only surviving, but also of minimizing heart damage following the attack.

Objectives
1. To analyse the cause of bottlenecks in the emergency care chain of cardiac in-patient flow. The primary goal was to determine the optimal bed allocation over the emergency care chain, given a required service level (max. 5% refused admissions).
2. To provide further insight into the relation between natural variation in arrivals and length of stay and occupancy rates.

Setting
Emergency in-patient flow of cardiac patients in a university medical centre in Amsterdam. Computerized records of 2,813 patients entering the first cardiac aid (FCA) were used to describe patient flow. Approximately 90% of cardiac in-patient flow is emergent and therefore difficult to control. The average number of patients arriving per day was 7.8. Unscheduled arrivals at the FCA were modeled as a Poisson process with intensity $\lambda = 7.8$, which means that the inter-arrival times were exponentially distributed. The Poisson arrival assumption has been shown to be a good one in studies of unscheduled arrivals.[1]

Methods
This particular patient flow is characterized by time-varying arrivals at the FCA, the department where emergency cardiac patients enter the hospital. The strong variability of health care processes duration is

considered during modeling. The coefficient of variation (CV) of LOS is typically very close to 1.0. This motivated us to approximate the LOS with an exponential distribution. After accessing the FCA patients move to the coronary care unit (CCU) before they are discharged from the normal care clinical ward (NC). This study applies a stationary 2-D queueing system with blocking to analyze such congestion in emergency care chains.

Results, specific

1. Refused admissions at the FCA are primarily caused by unavailability of beds downstream the care chain.

2. Investment in expensive and flexible CCU beds is more cost-effective than increasing normal care bed capacity. This is counterintuitive.

Results, general

1. Variation in Length of Stay (LOS) and fluctuation in arrivals result in large workload variations at nursing units. Hence, flexibility in staffing levels is critical for maintaining operational efficiency.

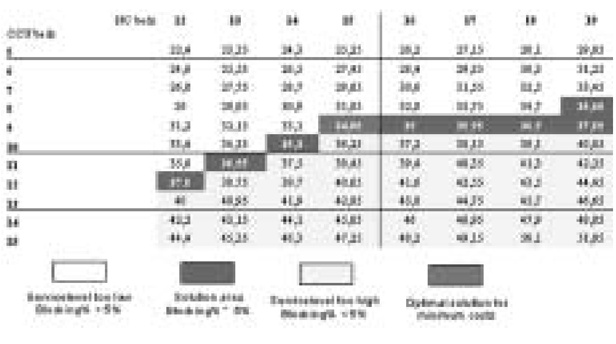

TABLE Relation between costs and bed distribution

2. The group of patients with extended hospital stay is relatively small but must not be neglected. In terms of total resource consumption (TRC) this group is critical for overall performance of the care chain.

3. Substantial buffer capacity is required to maintain blocking percentage under given limit.

4. The LOS of health care processes is not a constant of nature. The 'waiting time' can be as high as 20-30% of total LOS. This is often due to chain effects.

5. Larger service systems can operate at higher utilization levels than smaller ones while attaining the same percentage of blocking. Hence, in general merging departments has a positive effect on operational efficiency due to the economies of scale.

6. The strong focus on utilization rates of hospital management is unrealistic and counterproductive.

Conclusion

Operational Research techniques were successfully used in describing emergency cardiac in-patient flow. Bottlenecks have been identified and the impact of fluctuation in demand has been described. The optimal bed capacity distribution over the care chain for cardiac patients has been calculated.

References

1. Young, J.P. Stabilization of inpatient bed occupancy through control of admissions. J Am Hosp Ass 1965;39, 41-8
2. Green, L.V, Nguyen V. Strategies for cutting hospital beds: The impact on patient service. Health Services Research 2001;36,421-42

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REVIEW ARTICLE

A Canadian Network for Modeling and Simulation in Healthcare

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One of the main objectives of the Workshop was to bring together researchers and practitioners in simulation modeling from across Canada. We believe that there are a large number of people who are involved in research on a variety of modeling issues in healthcare. Many of them are in fact working on very similar problems.

We intend to pattern our activities based on a similar group in the UK called Mashnet. In September 2004, the Network in Healthcare Modelling and Simulation - Mashnet was awarded funding of around £60,000 for three years from the Engineering and Physical Sciences Research Council (EPSRC). The idea for this application originated at an Operational Research Society workshop on healthcare simulation in Reading in 2003. Many participants expressed the view that a network to co-ordinate the activities of those working in the area of healthcare modelling and simulation was sorely needed. Subsequently, there was circulation of the draft content of the application and a large number of supporting letters and comments were received.

Mashnet Aim

To improve the application of modelling and simulation techniques within healthcare decision making.

Mashnet Objectives

- To establish a small steering group which communicates on an on-going basis to facilitate the activities of the network. Ideally to include members from differing backgrounds.
- To create a dedicated web site to disseminate information, sharing of ideas and best practice.
- To organise regular (e.g., twice yearly) seminars of the membership to share experiences and ideas in healthcare modelling and simulation.
- To foster links and dialogue with other key organisations and special interest groups
- To develop a dedicated e-journal (pdf format distributed via the internet) and to promote the publication of papers and articles in the field of healthcare modelling and simulation.
- To establish a directory of practitioners in healthcare modelling and simulation in the UK.
- To build a comprehensive bibliography of healthcare modelling and simulation publications (for inclusion within the web site above).
- To develop educational resources to encourage learning of healthcare modelling and simulation for those with an active interest who could benefit. (e.g., web based resources)
- To stimulate the use of modelling in healthcare decision making through active dialogue with professionals in healthcare.

Progress to date

At the Vancouver workshop, we met to determine the level of interest in a Canadian network, and decide on the next steps. There were three members of the Mashnet steering committee present: Ruth Davies from Warwick, Sally Brailsford and Paul Harper from Southampton. They described some of the concepts and how their group was started. There was strong support for such a network. We felt that the group should provide an interface between modellers, clinicians, health managers and policy makers. Although the group will focus on Canadian priorities, we recognize the value of including international partners. We have begun to develop collaborative projects with Mashnet (developing a web-based bibliography of modelling papers and reports in healthcare).

Are you interested?
Anyone interested in working towards this association should contact Michael Carter: carter@mie.utoronto.ca.

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ORIGINAL ARTICLE

Don't panic - Prepare: Towards crisis-aware models of emergency department operations

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Summary
The existing models of Emergency Department (ED) operations that are based on the "flow-shop" management logic do not provide adequate decision support in dealing with the ED overcrowding crises. A conceptually different crisis-aware approach to ED modelling and operational decision support is introduced in this paper. It is based on Perrow's theory of "normal accidents" and calls for recognizing the inevitable nature of ED overcrowding crises within current health system setup. Managing the crisis before it happens - a standard approach in crisis management area - should become an integral part of ED operations management. The potential implications of adopting such a crisis-aware perspective for health services research and ED management are outlined.

Models as Tools for Better Understanding of Emergency Department Operations
Emergency departments (EDs) worldwide are becoming the dominant source of primary care and one of the main routes for admission into hospitals.[1,2] Large increases in presentations to emergency departments in recent years[3] that coincided with reduced healthcare budgets[1] have lead to frequent ED blockage crises characterised by considerably longer waiting times, ambulance diversion/bypass, and, ultimately, by compromised quality of patient care.

Simulation studies have formed a large component of the drive to understand and improve emergency department operations within the healthcare system. System Dynamics simulations have looked at the interaction of ambulance services with the ED and the role of hospital policy in ED patient treatment time4. Discrete Event Simulation of EDs have concentrated on either the scheduling of resources or the reduction of patient ED length of stay (LOS), assisting with identification of bottlenecks and other outcomes.[5]

In dealing with LOS issues, Discrete Event Simulation studies commonly attempt to break the ED into sub-units, assign patients to urgency categories and use these to prioritise access to resources. They generally approximate patient arrival rates and regulate patient flow by events such as completion of triage, admittance to an ED bed and review by doctors.[5-7] Discrete Event Simulations look at process level changes in the system and often assume that added resources contribute linearly to total throughput.

In trying to model the uncertain nature of ED operations, analysts have simplified the situation by grouping ED patients, developing unique process charts for each patient group (often including the duration of investigative activities such as imaging and tests, and the frequency of connections between the activities), and using generalised distributions to describe arrival rates, lengths of stay and treatment times in simulation and optimisation models.[8-9] Clinicians have grouped patient cases under the Casemix principle assuming that similar cases will be treated alike and utilise a particular set of resources.[10-11] Such groupings commonly suit situations where the range of cases is small, such as specialist departments, but have been less successful in EDs.

Thus, the prevailing modeling response to the complexity of the ED system has been to gather more data and build increasingly complex models. A large amount of effort has been focused on understanding ED dynamics and patient flows in order to promote efficient operation of the EDs and linked elements of the healthcare network. While delivering well-recognized benefits, many of the apparent solutions promote increased interactive complexity, making EDs more prone to certain kinds of crises.

Crisis-Aware View of Emergency Department

In 1984 Charles Perrow[12] published a book about the special characteristics of complex interlinked technological systems that make accidents in them inevitable. He analysed the way failures interact and the way systems are tied together with the objective of gaining a much better understanding of why accidents occur in complex ***tightly coupled*** systems such as nuclear power and chemical plants, and why they always will.

While EDs are not interlinked technological systems in the sense of the nuclear power plants in Perrow's examples, they are complex (as opposed to linearly interactive) and tightly coupled systems.

EDs as ***complex systems*** are characterised by:

- proximity of units not in production sequence (such as adjacent beds in an ED ward);
- common-mode interactions between components not in production sequence (one unit serving multiple processes - e.g. one ED nurse providing care to a number of patients in adjacent cubicles);
- having unintended feedback loops (e.g. the impact of an X-ray machine on patient queues or the impact of the number of patients waiting in ED beds for an admission to hospital on the number of patients in ED waiting area and their waiting time); and
- processes that are not fully understood (such as the time to stabilisation for particular patients).

EDs as ***tightly coupled systems*** have time dependent processes and invariant sequences of activities (e.g. patient care processes). Little interchange is possible between resources or between equipment during treatment and the overall design of the system only allows one way to reach the process goal (e.g. a particular treatment protocol).

The bad news is that these complexity and coupling characteristics of ED systems make crises such as ED blockage inevitable. To use Perrow's terminology, ED blockage is a normal accident. Rather than a statement of frequency, the term is meant to signal that, given the system characteristics, multiple and unexpected blockage accidents are inevitable and present an integral characteristic of the system.

The good news, though, is that the potential and real consequences of disruptive events have been the focus of crisis research for many years. A large pool of knowledge has been accumulated in the forecasting of infrequent disruptions, and the theory of crisis management is developing rapidly. A crisis-aware view of the ED that is based on blockage can tap into these knowledge bases, first in determining whether the system is simple or complex, then in understanding of the recurrence of blockage. If suitable precursors can be determined, then the forecasting of blockage crisis may be possible, for example, through data mining approaches.

What's Next: Health Services Research and ED Management Implications of a Crisis-Aware View

From both operations management and mathematical modeling perspectives, the ED as a crisis-prone system presents new challenges. Traditional models that attempt to explain large-scale behaviour in terms of small scales (e.g. individual patient characteristics or treatment) become inadequate in the region of boundary conditions for crises such as ED blockage. In fact, many traditional ED models have the potential to conceal the crisis event by failing to identify appropriate precursors and operating at too coarse or fine a level of detail. Making these models "crisis-aware" presents an important and exciting challenge for both health services researchers and management scientists.

From the ED management perspective, a crisis-aware modeling paradigm puts the "emergency management" back into the ED. It colours every aspect of management and changes attitudes towards ED effectiveness and efficiency. Once it is accepted that blockage crisis is inevitable, steps can be taken to manage it before it happens. The typical crisis manager's mantra of mitigation, preparedness, response and recovery can be applied to ED operations. This is a distinctly divergent view from traditional hospital administrative approaches and it can lead to different options in the structuring of, and providing resources for, the ED.

References

1. Duckett, S.J., D. Jackson,, B. Scully, Paying For Hospital Emergency Care, http://www.dhs.vic.gov.au/ahs/archive/emerg/index.htm#Contents, Acute Health Division, Department of Human Services, Accessed: 26 Sep 2005
2. Bolton, P., M. Mira, and A. Sprogis, Oranges are not the only fruit: The role of emergency departments in care to primary care patients. Australian

Health Review 2000; 23: 132-6.
3. Cooke, M.W., S. Wilson, and S. Pearson, The effect of a separate stream for minor injuries on accident and emergency department waiting times. Emerg Med J 2002;19: 28-30.
4. Lane, D.C., C. Monefeldt, J. Rosenhead, Looking in the wrong place for healthcare improvements: A system dynamics study of an accident and emergency department. JORS, 2000;51:518-31..
5. Miller, M.J., D.M. Ferrin, M.G. Messer. Fixing the emergency department: A transformational journey with EDSIM. Proceedings of the 2004 Winter Simulation Conference: INFORMS 2004.
6. Coats, T.J., Michalis,s. Mathematical modelling of patient flow through an accident and emergency department. Emerg Med J 2001;18:190-2..
7. Brailsford, S., L. Churilov, S.K. Liew. Treating ailing emergency departments with simulation: an integrated perspective.. Proceedings of International Conference on Health Sciences Simulation,. Orlando, Florida: The Society for Modeling and Simulation International 2003.
8. Bagust, A., M. Place, J.W. Posnett, Dynamics of bed use in accommodating emergency admissions: stochastic simulation model. BMJ 1999;319:155-8.
9. Hoffenberg, S., M.B. Hill, and D. Houry, Does sharing process differences reduce patient length of stay in the emergency department? Annals of Emergency Medicine 2001;38: 533-40.
10. Jelinek, G.A., A Casemix information system for Australian Hospital Emergency departments, Perth: A Report to the Commissioner of Health, Western Australia. 1995
11. Bond, M., et al., Urgency, disposition and age groups: A casemix model for Emergency Departments. EMA 1998;10:103-10.
12. Perrow, C., Normal Accidents. Basic Books, New York, 1984.

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ORIGINAL ARTICLE

Beginning patient flow modeling in Vancouver Coastal Health

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Summary
This paper reports on the development of patient flow modeling in Vancouver Coastal Health (VCH). The first section provides the context for the initiative. The organizational priority is then presented, with the project's purpose and goals. The initial models are briefly identified. The paper closes with examples of possible future directions for modeling in VCH.

Introduction / Context
Vancouver Coastal Health provides a range of health services from hospital treatment to residential, home health, mental health and public health services. The vision developed by the Senior Executive Team (SET) in late 2002 emphasizes access improvement and efficient service delivery particularly for One Acute Network. During 2003/04, VCH focused on budget challenges while also being committed to maintaining service levels.

Meanwhile, evidence continued to accumulate that residents of VCH experienced low rates of access as well as long wait lists for surgical and other services. VCH also recognized bottlenecks at the front and back doors of the region's hospitals. Patients admitted in the Emergency Room had long waits for beds, and Alternate Level of Care (ALC) patients often waited in hospital when they needed residential or other forms of care.

Modeling was beginning to appear in VCH as an analytical tool. Models had been used to identify requirements for ER stretchers and residential care beds. In addition, a research team from VCH and Providence Health Care (a major partner) had received significant funding and had begun to develop a major modeling laboratory.

One additional factor was pivotal in setting the stage. The CEO and CFO had had experiences in businesses that led them to value modeling as an applied research and development tool.

Patient Flow Initiative
These factors culminated in two important developments. First, patient flow was identified as a priority for 2004/05 and beyond. New teams were formed to improve access and throughput. However, the senior team felt that simulation modeling would strengthen the effort. Early in 2004/05, the CEO and CFO identified a Project Director for Patient Flow Improvement.

The purpose for the new project was to improve patient flow using an overall systems perspective by drawing on simulation modeling and other process improvement techniques.

The goals of the project were to:
- Provide timely access and service.
- Optimize resource use to increase the individuals served.
- Reduce resources spent managing gridlock.
- Reduce patient/client/resident delays.

Before the 2005/06 fiscal year, the SET established new organizational targets to reduce:
- Wait time in ER for admitted patients, for surgery and for residential care
- Surgical cancellations
- Length of stay
- Alternate level of care (ALC) rates

Patient flow modeling is expected to be instrumental in achieving these targets.

Initial Models and Applications
In the first year and a half, the Patient Flow Project has undertaken the development of four models.

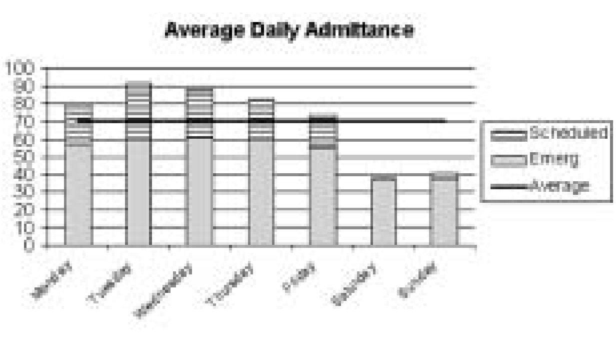
The ***System Model*** takes a high level view beginning with acute care and moving through major community services. Applications will include examining the effect of changes in the capacities of Transitional Care, Residential Care and Home Support services on ALC rates.

The ***Unit Allocation Module*** generates optimal allocations of beds to physician service groups given actual arrival and service patterns and targets for various utilization improvements. Applications will include supporting redevelopment of the hospital bed map.

The ***Daily Bed Management Model*** examines daily and hourly factors and weekday/weekend differences affecting flow through beds, such as delays in diagnostic tests and physician consults, and availability of rehabilitation therapy staff and staff to process admissions and discharges. This model will be used to examine the effects of reducing the variation in arrival rates during weekdays as well as for weekdays vs weekends.

The ***Surgical Resource Optimization Model*** addresses patient flow through the Operating Room (OR) theatres and surgical beds. This model will be used to develop scheduling guidelines and assist in revising the surgical block schedule.

It has been instructive to learn that admissions through emergency are comparatively consistent from Mondays through Fridays, whereas scheduled admissions are quite different by day of the week, as illustrated in the following diagram. At VCH's largest hospital, the average daily admissions through the ER range from 55 to 61 on weekdays, and 37 on weekends. Scheduled admissions, however, range widely from an average of 19 to 32 on weekdays.



This suggests why the idea of smoothing arrival rates is promising.

Typical Principles
Three broad principles have been identified as fundamental to the patient flow improvement efforts at VCH:

- Take a system view. The Institute for Health Improvement (IHI) is a strong advocate of broadening the field of view when examining flow issues.[2]
- Smooth variations in arrival patterns, service patterns and discharge patterns. This idea is the basis for two of the top ten high impact changes recommended by the UK NHS Modernisation Agency (superceded by the NHS Institute for Innovation and Improvement).[3]
- Reduce segmentation[4]

The models will be used to analyze scenarios based on these principles. By working with operational teams, the findings are expected to influence changes in policy and practice.

Questions for Applied Research
The patient flow improvement project team is expected to continue to develop new tools, some in collaboration with research colleagues. Several of the VCH operational and research models address surgical services. The following topics illustrate possible directions for future applied research in surgical modeling:

- Impact of delays in service on patient health outcomes (e.g., adverse events while waiting)
- Finding the weekdays/weekend balance in terms of patient demand, staff availability, and system resources.
- Evaluating surgical ambulatory services - including the impact on system flow.
- Finding the right mix of general and specialized resources in relation to throughput and patient outcomes.

Conclusion
Vancouver Coastal Health has taken the innovative step of using simulation modeling to support improvement in patient flow. The experience of key executives who had used modeling in other industries was a key factor in this undertaking. Several promising models have been developed, and key principles have been identified to guide scenario development and analysis. There are numerous patient flow questions that lend themselves to simulation modeling.

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ORIGINAL ARTICLE

Mathematical methods to assist with hospital operation and planning

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Summary
Within health Operational Research, the use of 'computer package' methods such as simulation and system dynamics is becoming so prevalent that it feels somewhat old hat to use analytical methods to develop explicit mathematical formulae or even to explore the mathematical structure of problems. This paper will discuss the use of such 'back of the envelope' analysis illustrating its usefulness. It will be shown that not only does this approach yield considerable insight, but also that it can give rise to powerful and practical solution methods. Examples of this will be discussed in relation to issues such as bed needs estimation, admissions and facilities planning.

The author is Director of the Clinical Operational Research Unit (CORU) which was established in 1983, receiving core funding from the UK Department of Health. The concept of a full time university-based research unit dedicated to applying expertise in Operational Research (OR) to problems in health care provides a relatively rare research resource. Yet, the scope for such research, applied to an increasing range of health care activity, is enormous. Issues such as treatment evaluation, performance measures, clinical governance, evidence based medicine and health service delivery are all amenable to OR. Further, OR often provides an immensely cost effective alternative to traditional methods of clinical research based on randomised controlled trials or large scale epidemiological studies.

The nature of OR, and one of its main strengths, is that it encompasses a wide range of analytical and scientific methods. Mathematical modeling, statistics, computer-based methods, trial design and analysis all contribute to health OR and, under both of its Directors since 1983, a conscious effort has been made within CORU to foster a diversity of research methodologies. Particular emphasis is put on developing new mathematical methods and computer software. This is somewhat at odds with what seems to be a growing trend in health OR towards researchers specialising in just one or two areas of methodology; thus Tom does queueing theory, Dick does simulation and Harry does System Dynamics. Of course there are exceptions, but for whatever reason, the trend towards specialisation seems real.

In this paper, benefits of a more diverse approach to health OR is advocated, particularly the use of 'back of envelope' mathematical methods as an alternative to the use of proprietary software packages. Three case studies are described to illustrate this approach.

In praise of diversity in Operational Research
Perusing any general textbook on OR, one can see it is undoubtedly a very diverse subject. The author has a useful analogue when teaching, describing OR as a filing cabinet drawer containing a range of different techniques, for example those listed in Table 1. Part of the skill of OR is finding out from the client what the practical problem is and then determining which particular technique to access from the filing cabinet. The difficulty (and joy) of OR, is that one really needs to be proficient in all these techniques.

Operational Research is characterised by the application of mathematical and computer based modeling to practical problems. By accident, not design, the author had experience of both before joining CORU. Initially, his research was in pure mathematics spending vacations employed in a work study department of a factory (an excellent grounding for OR). He then

TABLE 1. Examples of the diversity of methodologies applied to healthcare problems within the Clinical Operational Research Unit indicating the perceived prevalence of the application of such techniques in health OR in general.

Operational Research methodology	*Perceived prevalence in Health OR*	*Example of projects carried out by CORU*
Deriving equations	Low	Bed demand estimation[1,2]
Discrete Decision analysis	High	Cardiac surgery[3]
Statistical modeling	Low	Monitoring outcomes in surgery[4,5,6]
		Development and testing of risk models[7]
Optimisation	Low	Admissions planning[8]
Queueing theory	Low	Analysis of waiting lists[9]
		Patient progress modeling[10]
Stochastic analysis	Low	Evaluation of screening programmes[11]
		Health impact assessment [12]
Deterministic compartmental modeling	High	Modeling cancer chemotherapy[13]
Simulation	High	Prioritised booking systems[14]
Software development	Low	Clinical decision support systems[15]
		Clinical audit systems[16]
When all else fails, invent something	Low	Assessment of runs of poor outcome[17]
		Advising a Public Enquiry[18]
		Antenatal screening[19]

spent some ten years involved in traffic and transport research, the majority of this developing and evaluating computerised road traffic control systems. This chaotic career path eventually led to joining CORU, a Unit with a wealth of experience of applying a wide range of mathematical modeling techniques, as illustrated in Table 1. This reinforced the appreciation of the merits of diversity

Insofar as the author has a methodical approach to research, it is to start with mathematics and, if that fails, to then turn to the computer. This approach appears to be becoming somewhat unusual. However, what are the advantages of considering mathematics before computer based methods? The following can be cited:

- there are numerous very powerful mathematical techniques that have been developed over many centuries;
- mathematics provides insight;
- applying mathematics forces one to think about the key elements of a problem and to avoid unnecessary detail;
- there are many problems that simply are not amenable to analysis using proprietary software packages;
- sometimes it is just more fun to try something new than something tried and tested.

It is not the intention of this paper to provide a more lengthy discussion of the pros and cons of more mathematically oriented OR than already indicated. However, hopefully, the examples given in the following sections will illustrate the usefulness of such an approach.

Case study 1. A policy of booked admissions requires additional capacity.

This research stemmed from a short study concerning the policy of booked admissions being introduced to the UK health service. CORU undertook a short exercise of 'back of envelope' analysis which established that variability in length of stay was a central issue (which at the time did not seem to have occurred to policy makers) and, inevitably, this would lead to additional capacity requirements if booked admissions were introduced. The model derived was as simple as it could be made. A surgical unit was assumed to book N admissions per day, all of whom attended. It was assumed that there were no emergency admissions and that the only source of variability concerned length of stay, assuming a homogeneous patient population, with pi representing the probability that a patient would still be resident on the i-th day after admission. It is not too hard to establish that the steady state probability of k beds being required on any given day is the coefficient of x^k in the power series.

$$Q(x) = \left(\prod_{i=0}^{\infty} \left[(1 - p_i) + p_i x \right] \right)^N . \qquad (1)$$

Without taking variability into account, bed requirements would be estimated as N times the mean length of stay, however the implications of (1) are that such a level of bed provision would frequently lead to overload. Indeed to reduce the chances of such overload to reasonable levels would require the provision of some 25% reserve capacity.

A paper on this appeared in the BMJ1, possibly the first time this august medical journal had published the phrase 'probability generating function'. The article also provoked angry response from government bodies, which at least indicated some degree of thought about it (indeed the importance of variability seems now to have been accepted).

Case study 2. Mathematical methods to assist with hospital operation

The simple analysis described above achieved its purpose, starkly illustrating to an influential clinical readership that variability affects capacity needs and establishing potential dangers of introducing booking policy without taking this into account. However, the analysis was not intended to assist real planning and for that one needs added realism.

In view of this, a stochastic model was developed[2,8] of bed needs in a single ward depending on a number of factors:

- numbers of booked admissions for H different health groups (HRGs), according to the day of the week (or some other planning cycle);
- mean numbers of emergency admissions depending on the day of the week;
- length of stay distribution depending on emergency/elective status, day of admission and HRG;
- 'Did not attend' rates, depending on HRG.

In the case of a unit adopting a regular (e.g. weekly) cycle of booked admissions, the following closed form analytical formulae were obtained for the mean, μ_d, and variance F ^2_d of the number of beds required on day *d* of a planning cycle of duration C days.

$$\mu_d = \sum_{h=0}^{H} \sum_{c=1}^{C} n_{h,c} \sum_{w=0}^{\infty} p^h_{c,(wC+d-c)} \qquad (2)$$

$$\sigma_d^2 = \sum_{h=1}^{H} \sum_{c=1}^{C} n_{h,c} \sum_{w=0}^{\infty} p^h_{c,(wC+d-c)} \left(1 - p^h_{c,(wC+d-j)}\right) + \sum_{c=1}^{C} n_{0,c} \sum_{w=0}^{\infty} p^h_{c,(wC+d-c)} \qquad (3)$$

Here for 1#*h*#*H*, $n_{h,c}$ corresponds to the number of patients from a particular HRG h booked for admission on day c of the planning cycle ($n_{0,c}$ corresponds to the mean number of emergency admissions). The quantities $p^h_{c,i}$ reflect the probability that a patient would still be resident i days after being booked for admission depending on the day of the cycle the booking is made and the HRG.

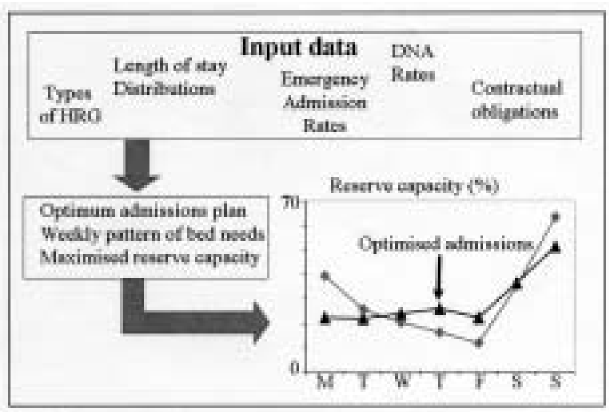

FIGURE 1. An illustration of the effects of optimal admission planning (triangles) compared with homogeneous admissions throughout the week (diamonds).

While equations (2) and (3) are apparently 'algebraic alphabet soup', they give considerable insight, (at least to those with sufficient mathematics) since they are linear in the variables $\{n_{h,c}\}$. Given this, it is possible to frame an optimisation problem[8] in order to determine the pattern of in-patient admissions. A natural objective is to minimise the maximum expected bed overload during the planning cycle, constraints corresponding to the numbers of patients from different HRG s who need to be treated. Figure 1 illustrates the outcomes of using such an optimisation method based on hypothetical but realistic data. This illustrates the way in which 'back of envelope methods' sometimes allow one to harness very powerful mathematical techniques.

Case study 3. Mathematical methods to assist with hospital planning

The final example indicates how the analysis methods discussed in the previous sections can be extended to assist with another important problem, hospital planning related to the identification of bottlenecks within the system. Here the issues go beyond the operation of a single ward or unit and concern the progression of patients through a succession of care

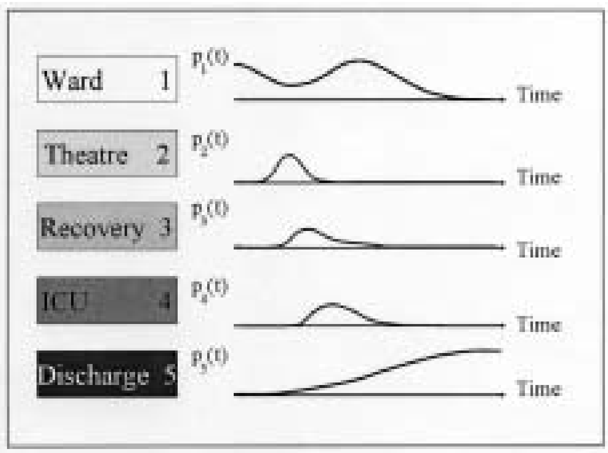

FIGURE 2. Probabilities associated with patient location dependent on the time since admission.

processes within a hospital, each taking place within distinct locations. An example of this is cardiothoracic surgery where patients move from ward to operating room to a recovery room, or possibly an intensive care environment, then back to a ward prior to discharge.

Here, given sufficient data, one can in principle typify a patient's journey through the care process in terms of location-probability distributions as illustrated in Figure 2.

In more general terms, consider an underlying pattern of booked admissions that is cyclic, with a planning cycle of C days, of patients from H different HRGs. In a manner similar to the analysis used to derive (1) and (2), analytical expressions can be obtained for the mean and variance of the 'bed demand' in each of K different hospital locations, indexed *k*:

$$\mu_{d,k} = \sum_{h=0}^{H} \sum_{c=1}^{C} n_{h,c} f_{h,k}(P) \tag{3}$$

$$\sigma_{d,k}^2 = \sum_{h=1}^{H} \sum_{c=1}^{C} n_{h,c} g_{h,k}(P) \tag{4}$$

Here $f_{h,k}(P)$ and $g_{h,k}(P)$ represent closed form analytical expressions depending on the location probabilities shown in Figure 2. The exact form of these is complex and no doubt 'algebraic alphabet soup', however the importance of (3) and (4) is that they give a means of applying integer programming methods that enable one to establish where the system bottlenecks are and the potential effects of investing in new bed resources within the system. One such optimisation formulation is as follows:

Minimise z

Subject to:

$$R_h \le \sum_{c=1}^{C} n_{h,c} \qquad 1 \le h \le H \tag{5}$$

$$B_{d,k} z \ge \mu_{d,k} \qquad 1 \le d \le C, \quad 1 \le k \le K \tag{6}$$

$$0 \le n_{h,c}, \; n_{h,c} \text{ integer} \qquad 1 \le h \le H, 1 \le c \le C. \tag{7}$$

Here, constraint (5) requires at least a specified number (R_h) of patients from the *h*-th HRG to be booked for admission during each planning cycle. $B_{d,k}$ represents the number of beds provided of day *d* of the cycle at location *k* and constraint (6) ensures that 'reserve bed capacity' in each of the *K* hospital locations is maximised (and equalised as far as is possible).

Conclusion

Simulation and deterministic compartmental modeling are becoming increasingly prevalent in health related OR. Whatever the merits of these methods, OR has many other methods available and these should not be neglected. Examples are cited of numerous health related OR studies from the author's own experience that make use of alternative methods.

A number of specific case studies related to capacity requirements and hospital planning have been described that make use of mathematical methods including both stochastic analysis and optimisation, indicating the utility of adopting traditional 'back of envelope' methods of analysis.

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References

1. Gallivan S, Utley M, Treasure T, Valencia O. Booked inpatient admissions and hospital capacity: a mathematical modelling study. BMJ, 2002; 324:280- 2.
2. Utley M, Gallivan S, Treasure T, Valencia O. Analytical methods for calculating the capacity required to operate an effective booked admissions policy for elective

inpatient services. Health Care Management Science. 2003;6:97-104.
3. Treasure T, Chow T, Gallivan S. Replacement of the aortic root in Marfan's Syndrome. NEJ M. 1991;341:1473-4.
4. Lovegrove J, Valencia O, Treasure T, Sherlaw-Johnson C, Gallivan S. Monitoring the results of cardiac surgery by variable life adjusted display (VLAD). Lancet 1997;350:1128-30.
5. Gallivan S, Davis KB, Stark JF. Early identification of divergent performance in congenital cardiac surgery. Eur. J. Cardio-thoracic Surg. 2001;20:1214-9
6. Treasure T, Utley M, Bailey A. Assessment of whether in-hospital morality for lobectomy is a useful standard for the quality of lung cancer surgery: Retrospective Study. BMJ 2003;327:73-4.
7. Berrisford R, Brunelli A, Rocco G, Treasure T, Utley M, The European Thoracic Surgery Database project: modelling the risk of in-hospital death following lung resection, Eur. J. Cardio-thoracic Surg. 2005;28:306-1.
8. Gallivan S, Utley M. Modelling Admissions Booking of elective in-patients into a treatment centre. IMA J. Management Math. 2005;16:305-15.
9. Goodyear OM, Gallivan S, Sozou PD, Can queuing theory be applied to hospital waiting lists? Current Perspectives in Healthcare Computing. BJHC Books 316-324. ISBN 0 948 198 26 5, 1998.
10. Pearce RM, Gallivan S, Jackson RRP. Patient progress modelling for small cell lung cancer. Eur. J of Cancer. 1993; 29: 734-7.
11. Sherlaw-Johnson C, Gallivan S, Jenkins D. Withdrawing low risk women from cervical screening programmes: mathematical modelling study', BMJ. 1999;318:356-60.
12. Utley M, Gallivan S, Biddulph J, McCarthy M, Ferguson J. ARMADA - A computer model for the impact of environmental factors on health. Health Care Management Science 2003;6:137-46.
13. Birkhead BG, Rankin EM, Gallivan S, Dones L. A mathematical model of the development of drug resistance to cancer chemotherapy. Eur.J. Cancer& Clinical Onc. 1987;23:1421-7.
14. Tuft S.Gallivan S. Computer modelling of a cataract waiting list. Brit. J.Ophthalmology. 2001 85 582-5.
15. Sherlaw-Johnson C, Gallivan S, Patterson DHL, Treasure T. Two computer systems to assist with the clinical management of patients with coronary artery disease. Eur. Heart Journal. 1996;17:232.
16. Leaning MS, Gallivan S, Newlands ED, Dent J, Brampton M. A computer system for assisting with clinical interpretation of tumour marker data. BMJ. 1992;305:804-7.
17. Gallivan S. How likely is it that a run of poor outcomes is unlikely? Eur. J. Op.Res. 2003;150:46-52,
18. Gallivan S. Assessing morality rates from dubious data - when to stop doing statistics and start doing mathematics. Health Care Management Science. 2005;8:237-41,
19. Utley M, Gallivan S. Evaluation of strategies for Downs Syndrome screening. Journal of the Operational Research Society. 2000;51:272-7.

ORIGINAL ARTICLE

Modeling Change in A Health System: Implications on patient flows and resource allocations

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Summary
This work is motivated by the recent changes in the health system in Turkey, which is a consolidation of health insurance funds, and its implications on the resource allocations and the flow of patients in the system. Our aim is to provide a model to find the best reallocation of resources between the hospitals and the best patient-hospital match to minimize the costs.

Introduction

In this paper, we consider a problem motivated by the current reform efforts in the Turkish health system. This transformation involves consolidating the existing public health insurance systems. Currently there are four public insurance funds in Turkey that serve the working population and the poor.

The first step through this transformation involved the government acquisition of the 148 hospitals that were owned by one of the health insurance funds, SSK (social insurance association). It is obvious that when a network structure changes, the existing resource allocation structure may be sub-optimal. Hence, re-optimization of the whole system in order to match the resources better to patient demands at each location would be beneficial. However, transferring resources between hospitals at different locations brings a burden. In order to manage this change better, these "costs of change" should be taken into account in addition to the usual network costs of patient flows and capacity.

In this paper, we build a model to optimize hospital mergers and acquisitions. The objective is to minimize the cost of the new network and the cost of change subject to capacity and network flow constraints. Although the motivation of our problem comes from the Turkish health system, the problem is relevant for the health networks in other countries where mergers and acquisitions are seen often.

Literature Review

Papers in the related literature mostly use deterministic approaches. A common objective is the minimization of the travel cost, for which mathematical location-allocation models are proposed.[1-3] Stummer et al[4] used a multi-objective approach for the location-allocation decisions in a hospital network. Verter and Lapierre solved the problem of locating preventive health care facilities to maximize participation.[5] Few papers consider a stochastic environment although Chao et al used a nonlinear programming approach, with expected waiting time constraints,[6] whereas Harper et al used discrete-event simulation.[7]

Our model is also in a deterministic framework, but presents a more comprehensive approach than existing papers, accounting for both the travel costs and the resource transfer costs for many different resources in the same model.

The Model

Let H denote the set of hospitals, R the set of resources, S the set of services, $R_S \geq R$ the set of resources required for service s, S and P the set of population centers. The parameters of the problem are as follows.

H_i: the set of hospitals to which resources can be transferred from hospital i H

C_{ri}: the amount of resource r , R at hospital i , H

k_r: the number of patients that a unit resource r, R can serve

T_r: the amount of space that a unit resource r, R takes in a hospital

D_{ks}: the number of patients in population center k, P who need service s, S

t_{ki}: the cost of travel from population center k, P to hospital i, H

a_{rij}: the cost of transferring a unit resource r, R from hospital i, H to hospital j, H.

b_{ri}: the cost of buying one unit of resource r, R at hospital i, H

F_i: the fixed cost of expanding capacity of hospital i, H

K_i: the available space at hospital i, H

K'_i: the extra space that will be added if there is an expansion at hospital i, H

κ_s: the minimum capacity that service s, S should have

m_s: the minimum number of patients that should be served by service s, S in any hospital

ψ_{si}: the maximum acceptable ratio of demand to capacity for service s, S at hospital i, H.

Define x_{rij} as the amount of resource r, R transferred from hospital i, H to hospital j, H and p_{ri} - the amount of resource r, R purchased at hospital i, H. Define also z_{ksi} as the number of patients from population center k, P assigned to hospital i H for service s, S, and E_{si} as the final capacity of service s S at hospital i, H. Let u_{si} i{0,1} be 1 if service s, S exists at hospital i, H and 0 otherwise, and y_i {0,1} to be 1 if the space of hospital i, H is expanded and 0 otherwise. Then, the problem is modeled as follows:

$$\min \sum_{r\in R}\sum_{i\in H}\sum_{j\in H_i} a_{rij}x_{rij} + \sum_{r\in R}\sum_{i\in H} b_{ri}p_{ri} + \sum_{i\in H} F_i y_i + \sum_{k\in P}\sum_{i\in H} t_{ki}\sum_{s\in S} z_{ksi} \tag{1}$$

s.t.

$$\sum_{j\in H_i} x_{rij} \leq C_{ri} \qquad \forall r\in R, i\in H \tag{2}$$

$$\sum_{i\in H} z_{ksi} = D_{ks} \qquad \forall k\in P, s\in S \tag{3}$$

$$\sum_{s\in S: r\in R_s} E_{si} \leq \kappa_r (C_{ri} + p_{ri} + \sum_{j\in H: i\in H_j} x_{rji} - \sum_{j\in H_i} x_{rij}) \qquad \forall r\in R, i\in H \tag{4}$$

$$\sum_{k\in P} z_{ksi} \leq \rho_{is} E_{si} \qquad \forall s\in S, i\in H \tag{5}$$

$$\sum_{r\in R} \omega_r (C_{ri} + p_{ri} + \sum_{j\in H: i\in H_j} x_{rji} - \sum_{j\in H_i} x_{rij}) \leq K_i + K'_i y_i \qquad \forall i\in H \tag{6}$$

$$E_{si} \geq \varepsilon_s u_{si} \qquad \forall s\in S, i\in H \tag{7}$$

$$\sum_{k\in P} z_{ksi} \geq m_s u_{si} \qquad \forall k\in P, s\in S, i\in H \tag{8}$$

$$z_{ksi} \leq D_{ks} u_{si} \qquad \forall i\in H \tag{9}$$

$$y_i \in \{0,1\} \qquad \forall\ i\in H \tag{10}$$

$$u_{si} \in \{0,1\} \qquad \forall\ s\in S, i\in H \tag{11}$$

$$p_{ri} \in Z_+ \qquad \forall\ r\in R, i\in H \tag{12}$$

$$x_{rij} \in Z_+ \qquad \forall\ r\in R, i\in H, j\in Hi \tag{13}$$

$$zksi \in Z_+ \qquad \forall\ k\in P, s\in S, i\in H \tag{14}$$

The objective is to minimize the total cost (1) of resource transfer, resource purchase, hospital capacity expansion, and patient travel costs to the assigned hospitals.

Constraints (2) ensure that the amount of resources transferred from hospital i cannot be more than the existing amount. Constraints (3) imply that all demand is served. Due to constraints (4), the sum of final capacities of services using a resource cannot exceed the final amount of that resource; where the final amount of a resource is the previous amount plus the amount that is purchased plus the net amount of transfers. Constraints (5) state that the existing capacity (multiplied with a maximum utilization factor r#1 in order to have some slack capacity to cope with variability in the demand) for a service should be greater than or equal to the demand for that service, with a utilization factor. Total space requirement of the resources at a hospital should be less than or equal the available space of that hospital due to (6). For service s to exist in a hospital, it should have a capacity of at least e_s units and should serve at least m_s patients due to (7) and (8), respectively. Constraints (9) ensure that if a service does not exist in a hospital, no patient is assigned to that hospital for that service. Constraints (10)-(14) are integrality and 0-1 requirements.

TABLE 1: Results for eleven cities

Problem Case	*Total cost without resource transfer*	*Total cost with resource transfer*	*# Patient moves to another city*	*# Resource moves*
SSK	86,786,000	31,472,016	23,980	413
MoH	58,419,270	36,437,568	19,962	131
Sum of SSK & MoH (1)	145,205,270	67,909,584	43,942	544
Merged (2)	123,017,500	41,518,966	36,017	591
% Difference (1)-(2)	15	38	18	-8.6

Application of the Model

In this section the use of the model is illustrated with an application. The problem data is created from the data on Turkish hospitals in eleven cities given in the Statistics Yearbook 2004.[8] Three problem instances are compared in Table 1, which correspond to three different hospital networks: "SSK", "MoH" and "Merged" refer to the hospital network of the workers' insurance fund SSK, network of the Ministry of Health Hospitals, and the merged network, respectively. For this example, we assumed that there is no capacity expansion or resource purchase, hence the objective function consists of the patient travel and resource transfer costs only. The model is solved using CPLEX MIP Solver.

The results show that there is a significant opportunity of improvement by resource transfer after merging the two networks. If resource re-allocation is done, the total cost decreases by 38 % after the acquisition, at the expense of an 8.6 % increase in the resource moves.

Conclusion

We modeled the resource re-allocation problem to optimize the patient flows and demonstrated its use via an application in the Turkish health system. It was shown that there is significant potential of improvement by re-allocation of resources. Future research will focus on investigating the effect of the network structure on the potential benefits from mergers.

References

1. Chu S.C.K. Chu L. A modeling framework for hospital location and service allocation. International Transactions in Operational Research 2000;7:6:539-69.
2. Galvao R., Espejo L.G.A, Boffey B. A hierarchical model for the location of perinatal facilities in the municipality of Rio de Janerio. European Journal of Operational Research 2002;138:495-517.
3. Rahman S.U., Smith D.K. Deployment of rural health facilities in a developing country. Journal of the Operational Research Society 1999;50:892-902.
4. Stummer C., Doerner K., Focke A., Heidenberger K. Determining location and size of medical departments in a hospital network: A multiobjective decision support approach. Health Care Management Science 2004;7:63-71.
5. Verter V.,Lapierre S. Location of preventive health care facilities. Annals of Operations Research 2002;110:121-30.
6. Chao X., Liu L, Zheng S. Resource Allocation in Multisite Service Systems with Intersite Customer Flows. Management Science 2003; 49:1739-52.
7. Harper P.R., Shahani A.K., Gallagher J.E., Bowie C. Planning health services with explicit geographical considerations: a stochastic location-allocation approach. OMEGA 2005;33:141-52.
8. Statistics Year Book 2004. Ministry of Health of Turkey. http://www.saglik.gov.tr

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ORIGINAL ARTICLE

On comprehensive and realistic modeling: Some ruminations on the what, the how and the why

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Summary

This short paper is about comprehensive realistic modeling in general. I am no expert at all on health care or on modeling health-related systems. Rather, I am a computer scientist and, in recent years, have spent time applying some of my work on systems and software engineering to the modeling of biology. Indeed, the examples given in the talk are of two of our group's biological modeling projects. Nevertheless, I invited members of the audience to try to substitute "biology" for "health care" throughout the lecture. All I promised was that this experiment could yield interesting, perhaps thought-provoking, results. Towards the end I posed a "grand challenge" for the health-care modeling community.

The lecture emphasizes the two adjectives "comprehensive" and "realistic", as applied to modeling, and the questions it tries to deal with include:

- What kinds of systems should we model?
- Why do we want to model?
- How should we model?
- When are we done?

One of the main points made is to highlight the notion of *comprehensive* modeling – where the goal is to model an entire organ, an entire organism, or even an entire population – and to distinguish it from more conventional types of modeling, where one is interested in a specific aspect of a system and the modeling is aimed at getting particular results or making particular predictions. The motivation for comprehensive modeling is multi-fold. We really want to understand the system and to gain deep comprehension of how it works and of how it behaves over time, but we also want to predict its future behavior under varying circumstances, often ones that haven't yet been actually tried out in the laboratory.

It is obvious that comprehensive modeling, if carried out successfully, can yield very far-ranging benefits for biology and for science in general. However, its immediate benefits may be somewhat limited, since it is not designed to be a short term effort aimed at solving a particular problem.

The notion of *realistic* modeling is a key issue, and it is addressed throughout the lecture. To be realistic, a model must capture not only the overall viable stochastic behaviour of the system as a whole, but also the behaviour of the individual entities and their inter-relationships, their cooperation and their influence on each other. In fact, it is best if the model is such that the overall emergent picture be the result of the combined behavior of the individually modeled entities. A realistic model must be fully executable, which is more than carrying through a probabilistic computation of projected average case behaviour, or doing queuing theory analysis of probable outcomes. Executing the system is not just producing the end results, say, in the form of the probability of some event at the end of computing a Markov chain. Rather, we want the ability to execute the "program" of the system, which, just like running any computer program, can be done on various inputs, in a one-step-at-a-time debugging fashion, in ways that highlight the behaviour of individual pieces, in ways that take into account the probability distribution of inputs and of certain decisions made in the process, in best and worst case fashion, and indeed in typical average cases too. Thus, model execution should be the true analogue of running a conventional computer program, and model analysis is the analogue of verification, validation and complexity analysis.

Another aspect of the realism of the modeling has to do with ease of comprehension – both of the model itself and of its dynamics during execution. We want the experts of the subject matter (biologists when modeling biology, and in the present case perhaps health care researchers, hospital officials, and decision makers) to be able to model themselves or, at the very least, to comprehend and modify existing models. Thus, heavy use of differential equations or operations research theories and techniques in the modeling has the added disadvantage of being unfitting for use, or even modification by these experts, and indeed it can easily alienate them.

In way of illustrating the "realistic" facet of modeling, the lecture describes the general approach to modeling taken by our group. It is based on viewing the biological artifacts to be modeled as *reactive systems*[1], and to use for their modeling and simulating *visual formalisms.*[2] These are graphical, diagrammatic languages that are both intuitive and mathematically rigorous, and are supported by powerful tools that enable full model executability. They are linkable to object diagrams and GUIs, and other structural descriptions of the system under development and its front-end, as well as to full animation by an idea we call *reactive animation.*[3] At present, such languages and tools – often based on the *object-oriented* paradigm – are being strengthened by verification modules, making it possible not only to execute and simulate the system models (test and observe) but also to verify dynamic properties thereof (prove). They are also linkable to tools for dealing with the system's continuous aspects (e.g., Matlab) in a full hybrid fashion.

One of two variants of our approach is state-based, encouraging an *intra-object* style of specification, and uses the language of *statecharts*[4] to describe the system's behaviour by objects. One powerful tool supporting this is *Rhapsody*,[5,6] but there are many statechart tools. (Matlab has also adopted statecharts for its discrete aspects, in its *StateFlow* tool.) Another, more recent variant is scenario-based, and *inter-object* in spirit. It uses the language of *live sequence charts* (LSCs),[7] and allows one to play in the behaviour directly from the system's GUI and to then play it out just as if it were an intra-object model.[8] In both cases, the model's objects are considered to exist as individual entities, and when executed they interact with others in ways that are appealingly realistic.

The lecture then goes on to discuss a *Grand Challenge* that I proposed a few years ago to the computer science and systems biology community,[9] from which this paragraph and the next one are adapted. The challenge is to fully model an entire multi-cellular organism. We actually have a particular organism in mind, the *Caenorhabditis elegans* nematode worm, better known simply as *C. elegans*, a suggestion that is in line with the extraordinarily insightful 40-year old proposal of Sydney Brenner, who chose this creature to challenge biologists with the task of discovering the entire development and neurobiology of a living creature. (For this proposal and the tremendously influential work that he and others did following it, Brenner shared the 2002 Nobel Prize in Physiology or Medicine.)

This challenge – which we estimate to require many years of work by many research groups with diverse backgrounds, and which might never really be achieved – is to construct a full, true-to-all-known-facts 4-dimensional model of this worm (or of a comparable multi-cellular animal), which is easily extendable as new facts are discovered. The front end would be an anatomically correct, animated graphical rendition, tightly linked to a reactive system model of the entire creature. The model would be fully executable, flexible, interactive, comprehensive and comprehensible. It would enable realistic simulation of the worm's development and behaviour over time (the fourth dimension), which would help uncover gaps, correct errors, suggest new experiments and help predict unobserved phenomena. It would be zoomable, enabling easy switching between levels of detail (reaching down at least to the cellular level, and possibly the molecular level at some points), and allowing researchers to see and understand the organism and its behavior in ways not otherwise possible. The underlying computational framework would be not only rigorous and realistic, but would be set up in such a way that biologists would be able to enter new data themselves as it is discovered, and even plug in varying theses about aspects of behavior that are not yet known, in order to see their effects.

In order to lend support to this outlandish idea, the next part of the lecture describes briefly two modeling projects that we have been carrying out; one using the state-based intra-object approach and the other using (mainly) the scenario-based inter-object approach. The first project involves T-cell development in the thymus,[3,10] and shows thousands of cells entering the thymus, struggling and competing for the prize if becoming fully-fledged T-calls. This model was the motivation for developing reactive animation, and uses Flash linked with Rhapsody and its statecharts.

The second project involves vulval cell fate determination in the C. elegans nematode,[11,12] and its key players are six vulval precursor cells who have to decide which of them gets the honour of working with a special anchor cell to form the worm's vulva, which is its egg-laying venue. This model was built mainly from LSCs using the Play-Engine, but we have also done some verification work of cell mechanistic behavior against lab observations, using LSCs and statecharts.

At this point, I propose a Grand Challenge for this community. The challenge – in full analogy with the challenge for modeling biology[9] – is to model a complete health care system, fully and realistically. This could be "merely" an entire hospital, but my feeling is that it should be larger: perhaps the complete hospital system for a region or a state. It could, and possibly should, also include (or at least solidly interface with) other relevant entities, such as governmental health offices, medical schools, health insurance companies, etc. This kind of challenge – again, in full analogy with modeling a biological organism – is very long term and incredibly complex and might never be achieved. However, it also enjoys the same potential benefits, i.e., providing an unparalleled understanding of a vast system of relevance. If achieved, such a challenge will no doubt result in new ideas, predictions, and recommendations, that could help improve the overall quality of health care. Interestingly, truly grand challenges often yield significant advances even if they are not successful, simply by the massive amounts of work that come from the talent, energy, money and dedication concentrated around them.

The final part of the lecture addresses the particularly interesting question of how we know when we are done. Or, in other words, when is a comprehensive, realistic model deemed complete, or valid? Here I propose a sort of Turing test, but with a Popperian twist: a model of an entire biological system is complete and valid if a team of professionals cannot tell the difference between the model and the real thing.[13] There are many issues that have to be addressed for such a test to be even conceivable, such as the "buffer" that has to be set up to prevent the interrogating team from knowing the difference simply by peripheral things like sight and smell or the time difference between a computerized model answering a query and a lab experiment set up to do the same.

Of course, this test is perhaps too wild and far-fetched, almost imaginary, but it deserves discussion because it does try, just like Turing's original test for computerized intelligence[14] to put an upper bound on what is needed for comprehensive modeling to be complete. The Popperian twist comes from the fact that once such a model passes the test, it will inevitably change over time as science develops and we learn more about the system we are modeling – all this in the good spirit of Popper's philosophy of science.

Bibliography

1. Harel D, Pnueli A. On the Development of Reactive Systems. In: Apt KR, editor. Logics and Models of Concurrent Systems.New York: Springer-Verlag; 1985. p. 477-98.
2. Harel D. On Visual Formalisms. Communications of the ACM 1988;31:514-30.
3. Efroni S, Harel D, Cohen IR. Reactive animation: Realistic modeling of complex dynamic systems. Computer 2005 Jan;38:38-47.
4. Harel D. Statecharts: A visual formalism for complex systems. Sci Comput Program 1987;8:231-74. (Preliminary version: Technical Report CS84-05, The Weizmann Institute of Science, Rehovot, Israel, February 1984.)
5. Harel D, Gery E. Executable object modeling with statecharts. IEEE Computer 1997 ;30:31-42.
6. I-Logix web site. http://www.ilogix.com
7. Damm W, Harel D. LSCs: Breathing life into message sequence charts. Formal Methods in System Design 2001;19(1):45-80. (Preliminary version in Proc. 3rd IFIP Int. Conf. on Formal Methods for Open Object-Based Distributed Systems (FMOODS'99), (P. Ciancarini, A. Fantechi and R. Gorrieri, eds.), Kluwer Academic Publishers, 1999, pp. 293-312.)
8. Harel D, Marelly R. Come, Let's Play: Scenario-Based Programming Using LSCs and the Play-Engine. Springer-Verlag; 2003.
9. Harel D. A grand challenge for computing: Towards full reactive modeling of a multi-cellular animal. Bulletin of the EATCS 2003;81:226-35. (Reprinted in Current Trends in Theoretical Computer Science: The Challenge of the New Century, Algorithms and Complexity, Vol I, Paun, Rozenberg and Salomaa, eds., World Scientific, pp. 559-68, 2004.)
10. Efroni S, Harel D, Cohen LR. Toward rigorous comprehension of biological complexity: Modeling, execution, and visualization of thymic T-cell maturation. Genome Research 2003;13:2485-97.
11. Kam N, Harel D, Kugler H, Marelly R, Pnueli A, Hubbard E.J.A, Stern M.J. "Formal Modeling of C. elegans Development: A Scenario-Based Approach". Proc. 1st. Int. Workshop on Computational Methods in Systems Biology (ICMSB 2003), Lecture Notes in

Computer Science, Vol. 2602, Springer-Verlag, pp. 4–20, Feb. 2003. (Revised version in Modeling in Molecular Biology (G. Ciobanu and G. Rozenberg, eds.), Springer, Berlin, 2004, pp. 151–173.)

12. Fisher J, Piterman N, Hubbard EJA, Stern MJ, Harel D. Computational insights into Caenorhabditis elegans vulval development. Proceedings of the National Academy of Sciences of the United States of America 2005 Feb 8;102(6):1951-6.
13. Harel D. A Turing-like test for biological modeling. Nature Biotechnology 2005;23:495-6.
14. Turing AM. Computing Machinery and Intelligence. Mind 1950;59:433-60.

ORIGINAL ARTICLE

Combining Data Mining Tools with Health Care Models for Improved Understanding of Health Processes and Resource Utilisation.

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Abstract
Variability and uncertainty are inherent characteristics of most health care processes. Patient pathways and dwelling times even within the same process typically vary from patient to patient, such as the flow of patients through a particular health care provider or patient progression through the natural history of a given disease. The challenge for the OR modeller is to adequately handle and capture the stochastic features within developed models. This paper will discuss the benefits of combining patient classification tools (data mining techniques) with developed OR models, such as simulation tools, to more accurately capture patient outcomes, risks and resource needs. Illustrative applications will demonstrate the approach.

Introduction
Healthcare modeling is beset with many challenges.[1] A particular feature is the inherent variation and uncertainty in treating individuals. For example, length of stay in hospital or the infectious period for a given disease typically varies from patient to patient. From both a clinical and operational perspective, it is desirable to be able to understand and capture this variability.[2] Homogeneity leads to increased certainty in individual patient predictions (resource consumption, outcomes, pathways etc.), which in turn results in the potential for more effective and efficient planning and management of health care processes. In this paper we examine ways of incorporating data mining and patient classification techniques with healthcare models.

Proposed Framework
When designing and building health care models, there are a number of approaches when considering how to capture patient variability:

- Ignore variability: build deterministic models. Essentially here we have one patient group (all the available data) and are using average values.
- Re-sample all individuals. In this model we recreate every observed individual to exactly recreate real-life. This is time-consuming and still lacks the ability to provide insight for future predictions, such as case-mix or demand for services.
- Build a stochastic model with one "generic" patient group. In this model we define one distribution for each parameter I the model. We use all the available date to define each distribution, thus we are sampling individuals from the entire possible range of (observed) values.
- Create patient groups. Each patient group will have their own set of parameters, distributions, care-pathways etc.

The benefit of the last approach is that we are able to construct clinically and/or statistically meaningful patient groups that we can then use as patient groups in developed models in order to capture variability. As we create more groups, naturally we capture more of the variability and increase information content. However what typically happens that we reach a point when creating more patient groups does not lead to a further significant capture of variability or increased understanding. This is similar to Pareto's principle (80-20 rule). If we pursue the patient grouping approach, then we need to know how many groups to create and group definitions (e.g. for hospital length of stay we might create groups using indictors such as age, sex, elective or emergency, speciality etc.).

There are a number of statistical and data mining techniques that can help with the patient classification. These include regression, clustering methods, decision trees, neural networks and Bayesian networks. Intrasubject comparisons have been considered in the past, for example within statistics,[3] symbolic learning[4] and neural networks.[5] Other authors[2,6] have compared different algorithms for different types of datasets. The algorithms were evaluated using a number of criteria to measure the accuracy and the computing time taken to produce results, the comprehensibility of the results, as well as the ease of use of the algorithm to relatively naïve users. Research in this area indicates that there isn't a single best classification tool in practice but, instead, the best technique will depend on the features of the dataset to be analyzed and any end-user preferences. Decision trees, however, have been shown to be particularly robust and user-friendly.[2,6] In this paper we illustrate the proposed framework using decision trees, although the concepts could be equally applied to other data mining and classification techniques. Detailed information on decision tree algorithms will not be provided here, expect to say that there are numerous techniques including CART, CHAID, C4.5, C5.0 etc as well as various measures of *purity* (goodness of a split in the tree) which include Gini index, information entropy, least squares deviation and MaxDif. The reader is referred elsewhere7 for further details on the various approaches. Within the OR group at the University of Southampton, we have created decision tree software *Sparticus* that incorporates different algorithms and purity measures. We have developed new scaling algorithms for categorical variables and data handling approaches, which results in to fast software run-times and the ability to handle extremely large datasets.

Figure 1 shows a high-level schematic of the proposed combined data mining-modelling approach. First, we construct decision trees. The chosen dependent variable would be relevant to the nature of the patient-based model, such as dwelling time in a particular state of the patient pathway or probability of transition from one state to another. All patients will be assigned to one of the terminal nodes in the decision tree. Each terminal node becomes a unique patient group in the model. Here, we take the model to represent the individual patient pathways, such as movements through a health service provider or transitions through a natural history of a disease. Each individual patient that enters the model will belong to a patient group. Dwelling times and other parameters in the model will be taken from the group that the patient is a member of. To capture any dynamic effects, we may decide to create multiple decision trees for different parts of the model, and re-assign patients to groups as appropriate.

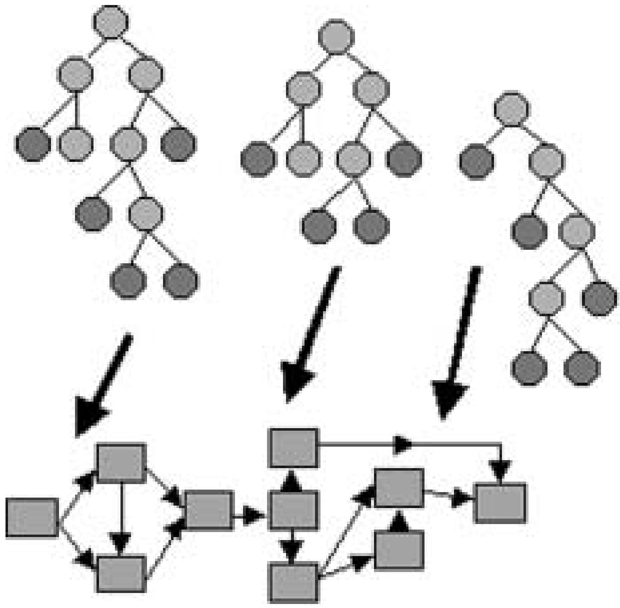

FIGURE 1. Combining decision trees (patient groups) with (patient-flow) models.

Illustrative Examples

The above framework has been adopted for various studies by the author. These include hospital capacities,[8] intensive care,[9] diabetic retinopathy[10] and screening for Chlamydia.[11] ue to limited space, here we discuss how the framework was successful used for modelling hospital resource capacities, such as beds, operating theatres and workforce.[8] The three-phase DES model called PROMPT model was developed to capture individual patient pathways through hospital and monitor corresponding resource needs. The challenge was to adequately handle the variability such as length of stay, operating times and workforce needs. A typical NHS hospital might have around 70,000 patients pass through a hospital in one year. Decision trees were constructed to define patient groups and fit

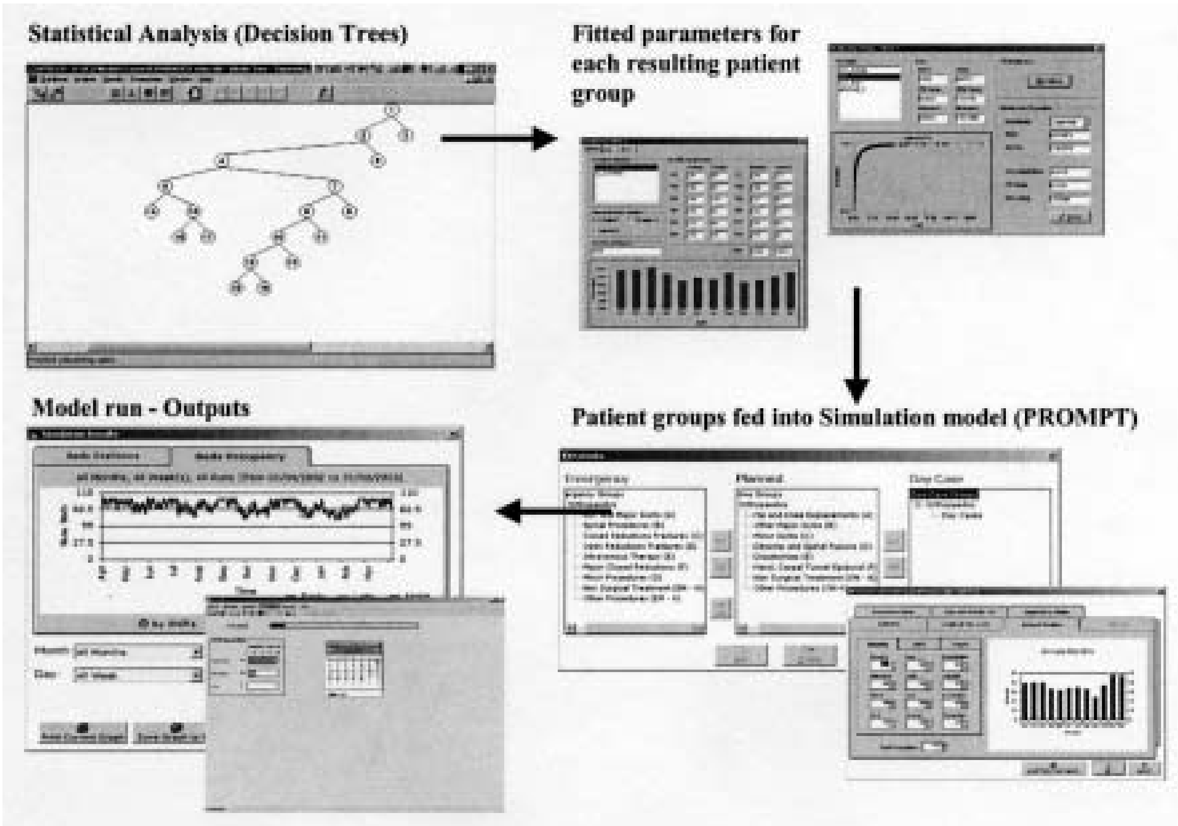

FIGURE 2: Illustrative use of the framework for modelling hospital capacities.

distributions for various parameters in the model. For example in one hospital we were able to define 15 patient groups that were then fed into the simulation model. Hospital managers could then change any of the parameters values for any of the 15 groups for scenario analysis, such as a reduction in length of stay or change in workforce needs for that patient group by skill-mix of staff.

Figure 2 illustrates the process of combining decision trees with the PROMPT simulation model through the use of actual model screen-shots. Furthermore, when validating the model by comparing model predictions to observed data, it was shown that capturing patients into 15 groups gave statistically significantly more accurate results than by simply using one patient group alone (with all patients in the model sampled from the same set of parameter values). Perhaps this may have been expected given the inherent variability between different patient groups in the hospital. Clearly, the ability to mimic more closely real-life patient flows and resource needs lies in the ability to capture patient groups with more homogenous model parameter values.

Discussion

Variability and uncertainty are inherent characteristics of most health care processes. Capturing the stochastic nature of such systems adequately, represents a challenge to healthcare modellers. Various approaches to dealing with patient-to-patient individuality may be explored. In this paper we propose a framework that combines data mining techniques with patient-based models. Patient groups are created which are in turn used as a basis to capture patient variability within developed patient-flow models. Individual patients are assigned to statistical and/or clinically meaningful patient groups. Model parameters are defined for each patient group, such as dwelling times and pathways.

The approach has been successfully used in a variety of healthcare settings, including both organisational and disease models. Future research will focus on improving the data mining techniques including scaling of trees, incorporation of fuzzy logic in the splitting criteria, incremental hybrid decision trees and on how to combine the best from neural networks, support vector machines, relation rules, decision trees etc. to create the concept of a "meta learner".

References

1. Harper PR, Pitt M. On the challenges of healthcare modelling and a proposed project life-cycle for successful implementation. Journal of the Operational Research Society 2004;55:657-61.
2. Harper PR . A review and comparison of classification algorithms for medical decision making. Health Policy 2005;71:315-31.
3. Remme J, Habbema JDF, Hermans J. A simulative comparison of linear, quadratic and kernel discrimination. Journal of Statistical Computer Simulation 1980;11:87-106.
4. Clark P, Boswell R. Rule induction with CN2: Some recent improvements. In: Kodrato Y. (ed.) Proceedings of ESWL'91, 1991 Springer-Verlag, Berlin, Germany, pp 151-63.
5. Xu L, Krzyzak A, Oja E. Neural nets for dual subspace pattern recognition method. International Journal on Neural Systems 1991;3:169-84.
6. King RD, Feng C, Sutherland A. Statlog: comparison of classification algorithms on large real-world problems. Applications of Artificial Intelligence 1995;3:289-333.
7. Murray SK. Automatic construction of decision trees from data: a multi-disciplinary survey. Data Mining and Knowledge Discovery 1998;2,345-89.
8. Harper PR. A Framework for Operational Modelling of Hospital Resources. Health Care Manag Sci 2002;5:165-73.
9. Costa AX, Ridely SA, Shahani AK et al, Mathematical modelling and simulation for planning critical care capacities. Anaesthesia. 2003;58:320-27.
10. Harper PR, Sayyad MG, de Senna Vet al. A systems modelling approach for the prevention and treatment of diabetic retinopathy. Eur J Operational Research 2003;150:81-91.
11. Evenden D, Harper PR, Brailsford SC and Harindra V. System dynamics modelling of Chlamydia infection for screening intervention planning and cost benefit estimation. IMA Journal of Management Mathematics 2005;16:265-79.

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ORIGINAL ARTICLE

Hillmaker: An open source occupancy analysis tool

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Summary
Managerial decision making problems in the healthcare industry often involve considerations of customer occupancy by time of day and day of week. We describe an occupancy analysis tool called Hillmaker which has been used in numerous healthcare operations studies. It is being released as a free and open source software project.

Introduction
Healthcare delivery systems such as hospitals and clinics are replete with flow related processes. Patients flow into and out of beds, surgical suites, procedure rooms, holding areas, and unfortunately, waiting rooms. Specimens and test results flow through various clinical processing areas, staff, material handling and even information systems. Many of these flow systems are characterized by both time of day and day of week effects with respect to arrivals, departures and occupancy. Furthermore, there usually is a great deal of uncertainty associated with the precise time of arrivals and departures as well as with the level of resources or capacity that will be needed to serve the demand. Managers of these systems are keenly interested in the arrival patterns of demand as well as the occupancy statistics representing the amount of work in their system since they are responsible for managing capacity, controlling costs and meeting desired customer service levels.[1,2] In this paper, we describe a database tool, called Hillmaker, which facilitates occupancy related analyses.[3] We have decided to release Hillmaker as a freely available, open source, software project under the GNU General Public License (http://www.gnu.org/copyleft/gpl.html).

Hillmaker
Hillmaker is a Microsoft Access add-in that can be used to create tabular and graphical summaries of arrival, departure and occupancy patterns by time of day for the following general problem. Some *entities* (e.g. patients, tests, samples, etc) flow into and out of some location (or state, stage, phase, etc.). A database table or query (view), called the *data source*, contains one record per entity. Each entity belongs to a *category* and has an *in date/time* and *out date/time* (or you can think of them as start and stop times). Each day of the week is divided into equally sized time bins such as hours or half-hours. Statistics of interest include the average, minimum, maximum and percentiles of the arrivals, departures and occupancy by time of day and day of week.

Example
Patients flow through a Short Stay Unit and from our hospital data warehouse we are able to obtain the date and times that each patient enters and exits the Short Stay Unit as well as the reason for their visit. The raw data is imported into a Microsoft Access database. For modeling purposes, each patient is classified each into one of five categories: ART (arterialgram), CAT (post cardiac-cath), MYE (myelogram), IVT (IV therapy), and OTH (other). We would like to create a graph that shows both the by category and overall average and 95th percentile of occupancy and the number of arrivals by time of day and day of week. Hillmaker makes it easy to create such graphs (Figure 1)

By modifying the raw data (perhaps, virtually via a query), one can even do some simple "what if" types of analyses. What would happen to the occupancy statistics if CAT patients did not use Short Stay and

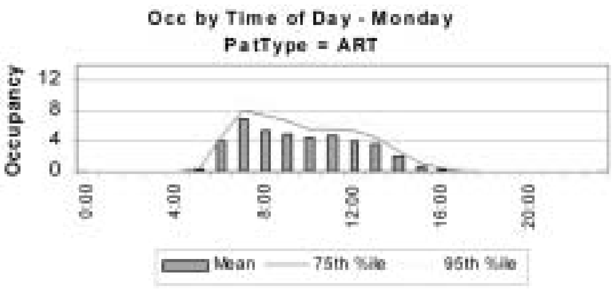

FIGURE 1. Occupancy graph example

instead recovered in a surgical recovery room? How is occupancy affected by a 25% reduction in length of stay?

The inputs for this software application, which was dubbed Hillmaker due to the hill-like nature of graphed occupancy statistics by time of day are: the name of the record source containing the transaction records, the date/time field corresponding to the entry time, the date/time field corresponding to the exit time, the field corresponding to the category, the date range for selecting transaction records for the analysis (the analysis period), and the time bin size (in minutes). The current version of Hillmaker has been implemented as a simple Microsoft Access based application consisting of the single user form.

The Hillmaker add-in outputs a number of tables containing the results of the analysis. The "ByDate" table contains the number of arrivals, exits and the occupancy for every time bin for each date in the analysis date range. In addition, separate summary tables are created for arrivals, exits and occupancy containing the various statistical measures by time bin by day of week. A spreadsheet based graphing template facilitates the creation of summary graphs.

Percentiles are extremely important performance measures for many service system planning problems. Bed sizing and staffing often rely on using some upper percentile of the distribution of occupancy or workload as a proxy for estimating the probability of insufficient capacity.4 Service level goals in call centres often take the form of a targeted percentage of calls answered less than some critical threshold time. As with most stochastic capacity planning problems, there is no "right" percentile to use for planning. Tradeoffs must be made between the cost of capacity and the cost of having insufficient capacity for demand. Calculating and reporting percentiles is the first step in addressing this inherent tradeoff. Hillmaker includes the capability to calculate percentiles using either the standard approach of using linear interpolation or using the lowest observed occupancy which is greater than or equal to the percentile desired.

Conclusion

The Hillmaker tool has been used in numerous projects involving occupancy related data in a wide range of healthcare subsystems including various inpatient units, emergency departments, appointment systems, outpatient clinics, transcription and billing departments, laboratories, and waiting rooms. It can be used for any type of customer service system in which arrival and departure times are available. Instructions for obtaining Hillmaker are available from the author (isken@oakland.edu).

References

1. K.M. Bretthauer, M.J., Cote, A model for planning resource requirements in health care organizations. Decision Sciences 1998; 29: 243-70.
2. V.L. Smith-Daniels, S.B. Schweikhart, D.W. Smith-Daniels, Capacity management in health care services: review and future research directions. Decision Sciences 1988; 19:889-919.
3. Isken, M.W. Modeling and analysis of occupancy data: A healthcare capacity planning application. International Journal of Information Technology and Decision Making 2002;1:707-29.
4. Green, L.V., How Many Hospital Beds? Inquiry Winter 2002/2003; 39: 400-12.

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ORIGINAL ARTICLE

The Challenge of Modeling Patient Safety Risk Management in a Complex Health Care Environment

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Health care systems can be extremely complex. They consist of interacting and constantly changing human and equipment elements. Thus, they are prone to incidents that may result in harm to patients. Baker and Norton recently reported that approximately 7.5% of hospital admissions result in adverse events.[1] This is unacceptable by any measure.

Change is occurring in most health care systems in the developed world to create a "culture of safety". Health care institutions have looked to industries such as the airline and chemical industries for examples of success in reduction of adverse events, and have made great strides. However, difficult methodological issues remain with regard to managing rare incidents that can be catastrophic in impact to both the "customers" and the industry itself.

This paper describes an ongoing research program designed to take a systems approach to an area of medicine that is particularly technologically intensive and complex: radiation oncology.[2-4] Treatment of cancer with ionizing radiation has clear benefits in terms of patient survival, but can be subject to systematic incidents which in some cases have resulted in hundreds of patients being exposed to inappropriate treatments.[5] The consequences can lead to severe disability or death. A major problem has been that, historically, a systems approach to risk management has not been applied, and no single person or unit in a particular institution has knowledge of the entire system; thus resulting in a classic scenario for incidents. Furthermore, although a large amount of human and financial resources are expended for quality control, there has no systematic process for efficient allocation of these resources, which is particularly important in a publicly funded government health care delivery system. The objective of our research program is to develop frameworks to inform these decisions.

Methods

The first step was the formation of a team of administrators and staff in a large cancer treatment institution in Alberta, Canada (the Tom Baker Cancer Centre, or TBCC). It became apparent that simple risk assessment methods that are currently being used in health care such as failure mode and effects analysis (FMEA) were not sufficient to inform quality control decisions. We therefore chose to employ more sophisticated quantitative methods including probabilistic risk analysis and decision analysis.[6]

Defining the problem and the system took considerable time, as this had never been done for the purpose of risk management in this particular institution. Our efforts resulted in a system map that provides the basis for quantitative modeling. As a first analysis we used influence diagrams to elucidate sources of uncertainty in cancer diagnosis and staging. We then took a taxonomic approach to define classes of incidents, to analyze existing data, and to help identify a causal structure. Simultaneously, we conducted a review of incident reporting systems, and have been implementing an inci-

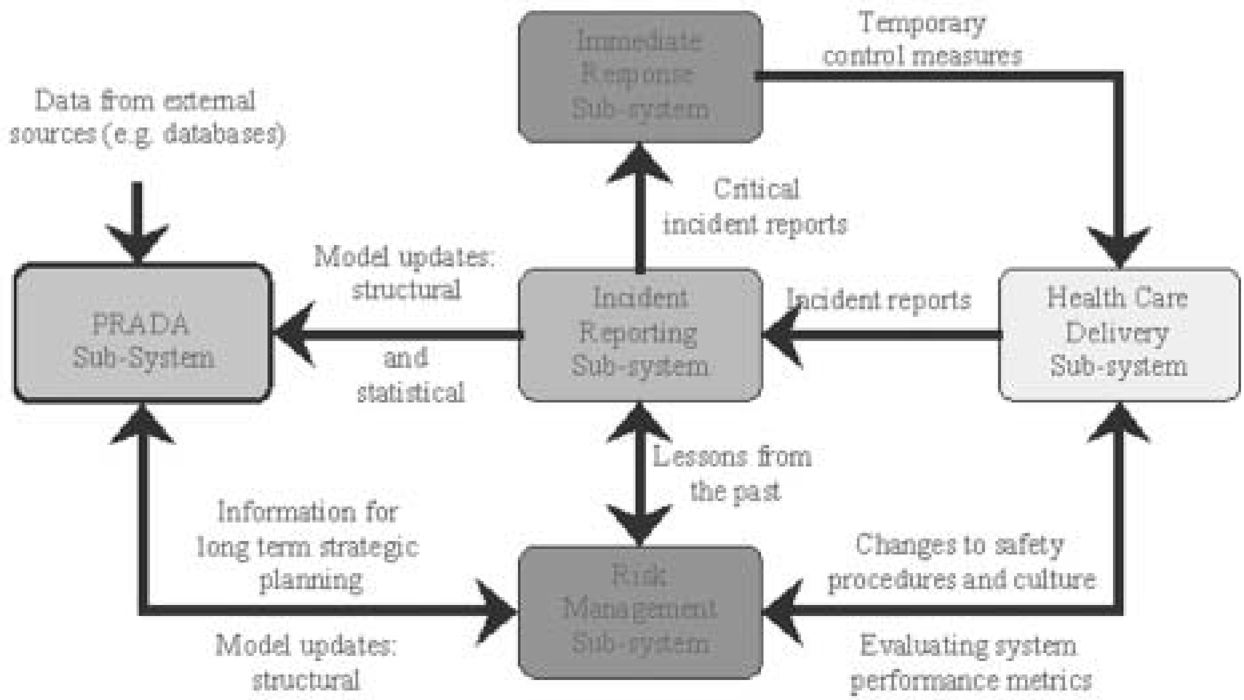

FIGURE 1: Integrated risk management approach (PRADA: Probabilistic risk and decision analysis)

dent tracking and learning system to inform the model and the organization, and vice versa. Figure 1 shows how this analysis framework is integrated.

Results

EXAMPLES:

1. Uncertainty in Diagnosis and Staging of Breast Cancer

Preliminary analyses[3,7,8] indicate that the probability of errors in diagnosis breast cancer is small but non-trivial. For example, the probability that a patient will be diagnosed as Stage III (i.e. advanced disease) when the patient is truly Stage III is approximately 82%, which implies that the probability the wrong stage will be assigned is 18%. The probability that a patient will receive 4-field treatment (i.e. a treatment protocol using 4 beams) when this is truly required is approximately 92%, which implies that the probability that the wrong treatment will be prescribed is 8%. Sensitivity analyses indicate that some common tests used for staging cancer contribute to overall uncertainty to an appreciable degree, and that specific combinations of tests can reduce uncertainty.

2. Taxonomy of Incidents

A taxonomic structure provides a framework for incident collection and processing. We developed a structure[9] that defines four classification criteria for incidents:

(1) Domain: Assessment, Prescription, Preparation, Treatment, and Follow-up;
(2) Source: Process and Infrastructure;
(3) Reproducibility: Systematic and Sporadic;
(4) Prescription elements: Dose and Volume.

To validate the taxonomic structure, incidents from publicly available sources were used to populate a database constructed to reflect the proposed structure. The incidents were further classified independently by four different users of the system. An analysis of the classification process revealed substantial agreement of the structure among the reviewers. Querying the database provided insights on the nature and relative frequency of incidents in radiation therapy, but the analysis also revealed that the lack of a standard framework for incident reporting makes it difficult to learn from existing incident report sources.

However, a clear understanding of the potential consequences and relationships between different incident types will guide the construction of improved incident collection frameworks, resource allocation and risk management efforts.

3. Incident Reporting/Learning Systems

We conducted a review of existing reporting systems,[10] and have designed a survey instrument for measuring both the safety culture and the organization's ability to learn from incidents.[11,12] We have administered this survey to TBCC staff prior to implementation of the new system, and we will repeat the survey each year post system implementation. The experimental group is staff in the radiation treatment program and the control group is other staff working in other programs at TBCC. We facilitated a cross-functional team of cancer centre staff who has designed a new system for learning from incidents.

Discussion

Our research has been invaluable to the cancer treatment administrators and professionals in understanding the system and the tradeoffs involved in risk management. The integrated tools and analyses that we have employed provide a means for knowledge translation and communication. The process of organizational change will take a long time, as most health care delivery individuals and institutions are not accustomed to systems thinking. We hope that our research will provide a model for other health care scenarios.

References

1. Baker GR, Norton PG. Adverse events and patient safety in Canadian health care. CMAJ 2004; 170:353-54.
2. Lee RC, Dunscombe P, Mobit P, Kelly KL, Brand K, Gray G, Currie G, Craighead P. An analytic framework for assessment of rare, catastrophic risks to radiation oncology patients. Proceedings of the Annual Meeting of the International Society for Risk Analysis, 2003, Baltimore, MD. www.sra.org.
3. Lee RC, Ekaette E, Kelly KL, Newcomb C, Craighead C, Dunscombe, P. A probabilistic model of catastrophic medical errors in radiotherapy. Proceedings of the Annual Meeting of the Society for Medical Decision Making, 2004b. Atlanta, GA. www.smdm.org.
4. Lee RC, Kelly KL, Newcomb C, Cooke D, Ekaette E, Craighead P, Dunscombe P. Quantitative approaches to patient safety: Research in risk analysis and risk management as applied to radiotherapy. 2004c. Alberta Heritage Foundation for Medical Research Health Technology Assessment Report series, www.ahfmr.ab.ca.
5. Cosset JM. ESTRO Breur Gold Medal Award Lecture 2001: irradiation accidents-- lessons for oncology? Radiother Oncol 2002;63:1-10
6. Cox LA. Risk Analysis: Foundations, Models and Methods. Kluwer Academic Publishers; 2002.
7. Lee RC, Ekaette E, Kelly KL, Newcomb C, Craighead C, Dunscombe, P. A linked influence diagram/Bayesian network model of risk management in radiotherapy. Proceedings of the Annual Meeting of the International Society for Risk Analysis, 2004a. Palm Springs CA. www.sra.org.
8. Lee RC, Ekaette E, Kelly KL, Craighead C, Newcomb C, Dunscombe P. Implications of cancer staging uncertainties in radiation therapy decisions. Medical Decision Making (in press)
9. Ekaette E, Lee RC, Dunscombe P. Risk analysis in radiation oncology: A taxonomic and causal structure. Proceedings of the Institute for Operations Research and the Management Sciences Annual Meeting, 2005. New Orleans, LA. www.informs.org.
10. Simon A, Lee RC, Cooke DL, Lorenzetti D. Institutional Medical Incident Reporting Systems: A Review. 2005. Alberta Heritage Foundation for Medical Research Health Technology Assessment series, www.ahfmr.ab.ca
11. Cooke, DL. Learning from incidents. In: Gonzalez, J.J., (Ed.) From Modeling to Managing Security - A System Dynamics Approach, pp. 75-108. Kristiansand, Norway: Norwegian Academic Press, 2003.
12. Cooke DL, Lee RC, Dunscombe P. A new approach to patient safety in the radiation treatment process for cancer. Proceedings of the Triennial Meeting of the International Federation for Operational Research Societies, 2005. Honolulu, HI. www.informs.org/Conf/IFORS2005.

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ORIGINAL ARTICLE

Categorizing Outcomes of Health Care Delivery

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Abstract

After a patient presents with symptoms of illness and undergoes treatment, there are three features of care that require assessment: the impact of delivering care on the patient, the benefits and harms of treatment, and the functioning of the health care system. This formulation leads to three types of outcomes of care delivery that require assessment: 1) patient outcomes, which reflect the impact on patients of undergoing care; 2) treatment outcomes, which reflect the intended and unintended medical consequences of undergoing therapy; and 3) system outcomes, which reflect the impact on the system of delivering health care to a group of patients. In this paper, examples of these three types of outcomes are presented, with particular reference to coronary artery bypass graft surgery. It is argued that the current focus of computer simulation models on system outcomes should be expanded to include patient and treatment outcomes.

Introduction

After a patient presents with symptoms of illness and undergoes treatment, there are three features of care that require assessment: the impact of delivering care on the patient, the benefits and harms of treatment, and the functioning of the health care system. This formulation leads to three types of outcomes of care delivery that require evaluation: 1) patient outcomes, which reflect the impact on patients of undergoing care; 2) treatment outcomes, which reflect the intended and unintended medical consequences of undergoing therapy; and 3) system outcomes, which reflect the impact on the system of delivering care to a group of patients. In this article, it is argued why each type of outcome should be assessed and present some limitations of each. Examples are drawn mainly from assessment of the peri-operative process for patients with coronary artery disease who are candidates for coronary artery bypass grafting (CABG). The peri-operative process is divided into three phases: the pre-operative phase which extends from assessment by a cardiac surgeon until admission to the cardiac nursing ward, the operative phase which extends from admission to the cardiac nursing ward until hospital discharge, and post-discharge. In the final section, the use of each type of outcome in computer simulation models of patient flow and several developments required to improve outcome assessment in simulation modeling are discussed.

Types of outcomes

Patient Outcomes

Patient outcomes reflect the impact on patients of undergoing care in a health care system. In countries having universal access to health care, wait lists are used extensively to manage access to many medical and surgical procedures as a means of improving efficiency.[1] For example, in Canada and other countries, patients with symptoms of coronary artery disease are assessed by a cardiologist and are sometimes referred to a cardiac surgeon. After assessment by the surgeon, patients who require CABG can either be admitted to hospital directly or, among patients for whom the operation can be safely delayed, registered on a wait list.[2-5] For the latter group, surgeons assign a clinically acceptable waiting time using established guidelines. One important patient outcome during the preoperative phase is the likelihood of undergoing CABG within the clinically acceptable waiting time (Table). Examples of other patient outcomes while on waiting for CABG include a deterioration of symptoms, an increase in urgency, or an unexpected emergency admission. Persons on wait lists for CABG have been shown to suffer from increased levels of discom-

TABLE. Examples of patient, treatment and system outcomes for patient flow modeling during the peri-operative process for coronary artery bypass grafting surgery.

		Phase	
Type of outcome	*Pre-operative**	*Operative***	*Post-discharge*
Patient	Immediate access /Direct admission /Access delayed longer than clinically acceptable time /Unexpected emergency admission /Adverse events while waiting (symptom deterioration, urgency increase) /Becoming not suitable for surgery	OR cancellation after admission /Noscomial infection /Patient safety indicators /Prolonged hospital admission /Early discharge	Unplanned readmission /Readmission after cancellation during hospital admission
Treatment	Adverse side effects or misadventure during coronary angiography /Detection of other comorbid medical conditions during anesthesiologist's pre-surgical assessment	Complications /Physiologic measures /Death	Improvement in angina symptoms /Prolongation of life
System	Wait time /Cancellation rate /Unused resources	Procedure numbers and rates Bed usage in CCU Length of stay	Readmission rate

* from assessment by a cardiac surgeon until admission to the cardiac nursing ward **from admission to the cardiac nursing ward until hospital discharge

fort and anxiety so that extended delays add to the patient's burden.[6]

After being admitted to hospital for CABG, an adverse patient outcome occurs when the planned operation is unexpectedly cancelled due to the operating room being reallocated to an emergency patient or becoming unavailable for other reasons. Patient safety indicators are receiving growing attention and, in some cases, such as for nosocomial infections, can be considered patient outcomes during the operative phase.[7] After recovery on the nursing ward is complete, if the patient cannot be discharged due to lack of a bed in a nursing home or of other resources, another patient outcome is a prolonged hospital admission.

The importance of assessing patient outcomes is that treating persons who are ill is the raison d'être of the health care system. Many policy changes that are implemented in hospitals are designed to have an impact on system outcomes. Without explicitly considering patient outcomes, it may not be possible to discern whether changes in systems outcomes have any effects on patients, whether beneficial or harmful.

Some limitations of patient outcomes relate to their interpretation. First, it may be ambiguous whether to classify an event as a treatment outcome or a patient outcome. For example, an unplanned readmission in the post operative phase for repair of the bypass graft or other reasons may constitute an adverse patient or treatment outcome. Second, it may be unclear whether or not an outcome benefits the patient. For example, early discharge could be the result of advanced planning (a good patient outcome) or could arise if scarce resources force patients to be discharged from hospital prematurely (an adverse patient outcome).

Treatment Outcomes

Treatment outcomes reflect the intended and unintended medical consequences of undergoing therapy. In the pre-operative phase for CABG, treatment outcomes can refer to the adverse events associated with diagnostic evaluation using coronary arteriography or detection of other co-morbid medical conditions during the anesthesiologist's pre-surgical assessment (Table). Adverse treatment outcomes during the operative phase include the risks of adverse events, including stroke or death. In some jurisdictions, operative mortality during CABG is used as an indicator of quality of care(8). CABG is undertaken to alleviate chest pain and increase survival and these are two intended treatment outcomes during the post-operative phase.

The importance of assessing treatment outcomes lies in the direct link with the goods and services that are being purchased. Also, there are often high quality data on intended effects of treatment and major unintended events such as mortality that are readily available. For example, health authorities in many jurisdictions routinely collect wait list registries for non-urgent surgical procedures that include information on dates of registration and removal, clinical information, operative reports, hospital discharge summaries and patient disposition.

Limitations of treatment outcomes include the following. First, the relationship between processes of care and treatment outcomes is poorly understood. For example, in a large study from the United States aiming to the relationship between processes of care during CABG and operative mortality and morbidity, the results pertained almost exclusively to operative factors that would not be amenable to improvement through policy changes.[9] Second, currently published treatment outcomes typically include mortality, morbidity, or objective measures of disease severity (e.g., chest pain). What matters to patients is functional status and quality of life.[10,11] Neither administrative data repositories nor disease-specific data collection systems such as CABG registries routinely include measures of functional status or quality of life. Third, typically only major unintended consequences of treatment are reported, while other, less disastrous, treatment outcomes which may have a large impact on quality of life are not recorded.

System Outcomes

System outcomes reflect the impact on the system of delivering care to a group of patients. In the pre-operative phase, studies of CABG have used as the outcome of interest, wait times within[2] or between[12] jurisdictions (Table). System outcomes, such as rates of operations per population, are compared between countries and within regions in the same country.[13,14] In another example of an international comparison of a system outcome, the length of stay for surgical procedures related to coronary artery disease for elderly patients was reported to be 33% lower in the United States than in Ontario and Manitoba.[15] In the post-operative phase, readmission rates for CABG have been compared between hospitals.[16]

There are several advantages of assessing system outcomes. First, routinely collected administrative data can be used for research on system outcomes. For example, abstracted summaries of hospital episodes are routinely collected in centralized repositories such as those maintained by the Canadian Institute for Health Information, the National Hospital Discharge Survey in the United States, and the Hospital Episode Statistics in the United Kingdom, as well as many disease and treatment registries. Second, system outcomes are straightforward to interpret. For example, numbers of hospital discharges, rates of surgical procedures, lengths of stay, or wait times can be interpreted directly, without invoking assumptions of unknown validity. Third, system outcomes may indicate deficiencies in health care. For example, in the United Kingdom, the National Service Framework for Coronary Heart Disease identified that the rate of CABG in England was unacceptably low and produced benchmarks for increasing the rate by a specific calendar date: between 2000 and April 2002, the total number of CABG procedures was to be increased such that the national rate would be 75 per 100,000 persons.[17]

Limitations of system outcomes have to do with their interpretation. First, how changes in system outcomes affect patient outcomes is usually unknown. Second, the interpretation of system outcomes often relies on assumptions that are difficult to substantiate. One common assumption is that higher rates of procedures lead to better treatment outcomes; the evidence supporting this assumption is often lacking. For example, rates of revascularization were compared among two cohorts of elderly survivors of acute myocardial infarction in the United States and Canada.[18] During the first 30 days after admission, rates of revascularization (including CABG and percutaneous transluminal coronary angioplasty) were eight times higher in one cohort than the other. Despite these differences in revascularization rates, one-year mortality was virtually identical in the two cohorts. Thus, the hypothesis that higher rates of revascularization procedures increased survival among elderly survivors of myocardial infarction was not supported by these data.

Outcomes in health care delivery models

Over the past several decades, health services and operations researchers have produced a substantial body of literature on computer simulation models of patient flow in health care.[19] To date, published computer simulation models has focused almost exclusively on system outcomes including: patient flow (patient scheduling and admissions; patient routing and flow schemes; scheduling) and allocation of resources (bed sizing and planning; room sizing and planning; staff sizing and planning).[20] Neither treatment nor patient outcomes have been incorporated into this type of simulation.

Including outcomes at all three levels - patient, treatment and system - into simulation models of patient flow requires methodological and conceptual developments. An important advance would be a taxonomy of outcomes and a knowledge base that assembles information and learning in this area. Incorporating all three types of outcomes into the decision-making process is another area of research that requires active investigation. Greater data collection efforts are required so that information repositories routinely include standardized measures of patients' interactions with the health care system, including their experiences in hospitals, and measures of functional status and quality of life.

The outcomes of patient interactions with the health care delivery system are becoming increasingly important indicators in health services research. Given the importance of evaluating all types of components of health care delivery, the impact of policy changes using simulation models should be expanded to include treatment and patient outcomes.

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References

1. Pierskalla WP, Brailer DJ. Applications of operations research in health care delivery. In: Pollock SH, Barnett A, Rothkopf MH, eds., Operations research and public systems. Amsterdam: Elsevier Science Publishers; 1993.
2. Levy AR, Sobolev BG, Hayden Ret al. Time on wait lists for coronary bypass surgery in British Columbia, Canada, 1991-2000. BMC Health Serv Res 2005;5:22.
3. Naylor CD, Sykora K, Jaglal SB, Jefferson S. Waiting for coronary artery bypass surgery: population-based study of 8517 consecutive patients in Ontario, Canada. The Steering Committee of the Adult Cardiac Care Network of Ontario. Lancet 1995;346:1605-9.
4. Kent GM, Power L, Gregory DM et al. Need for coronary artery bypass grafting in Newfoundland and Labrador: the impact of increased demand. Can J Cardiol 2004;20:399-404.
5. Seddon ME, French JK, Amos DJ, et al. Waiting times and prioritization for coronary artery bypass surgery in NZ Heart 1999;81:586-92.
6. Sampalis J, Boukas S, Liberman M, Reid T, Dupuis G. Impact of waiting time on the quality of life of patients awaiting coronary artery bypass grafting. Can Med Assoc J 2001;165:429-33.
7. Baker GR, Norton PG, Flintoft V, et al. The Canadian adverse events study: the incidence of adverse events among hospital patients in Canada. CMAJ 2004;170:1678-86.
8. Green J, Wintfeld N. Report cards on cardiac surgeons. Assessing New York State's approach. N Engl J Med 1995;332:1229-32.
9. O'Brien MM, Shroyer AL, Moritz TE, et al. Relationship between processes of care and coronary bypass operative mortality and morbidity. Med Care 2004;42:59-70.
10. Wilson IB, Cleary PD. Linking clinical variables with health-related quality of life. A conceptual model of patient outcomes. JAMA 1995;273:59-65.
11. Brazier JE, Johnson AG. Economics of surgery. Lancet 2001;358:1077-81.
12. Jackson NW, Doogue MP, Elliott JM. Priority points and cardiac events while waiting for coronary bypass surgery. Heart 1999;81:367-73.
13. Wennberg JE. Which rate is right? N Engl J Med 1986;314:310-1.
14. Blais R. Variations in surgical rates in Quebec: does access to teaching hospitals make a difference? CMAJ 1993;148:1729-36.
15. Anderson GM, Newhouse JP, Roos LL. Hospital care for elderly patients with diseases of the circulatory system. A comparison of hospital use in the United States and Canada. N Engl J Med 1989;321:1443-8.
16. Rumble SJ, Jernigan MH, Rudisill PT. Determining the effectiveness of critical pathways for coronary artery bypass graft patients: retrospective comparison of readmission rates. J Nurs Care Qual 1996;11:34-40.
17. National Service Framework for Coronary Heart Disease. 2000. London, UK National Health Service.
18. Tu JV, Pashos CL, Naylor CD, et al. Use of cardiac procedures and outcomes in elderly patients with myocardial infarction in the United States and Canada. N Engl J Med 1997;336:1500-5.
19. Fone D, Hollinghurst S, Temple M, et al. Systematic review of the use and value of computer simulation modelling in population health and health care delivery. J Public Health Med 2003;25:325-35.
20. Jun JB, Jacobson SH, Swisher JR. Application of discrete-event simulation in health care clinics: A survey. Journal of the Operational Research Society 1999;50:109-23.

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ORIGINAL ARTICLE

Toward Patient Centric and Distributed Healthcare Delivery Networks

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Greater patient centricity and intense distribution of services, responsibilities and authorities in healthcare delivery networks are worthy goals. Yet, moving from dreams and ideals to a working model and then to successful implementation, is challenging. This paper proposes a set of success factors based on the learning gained through an initiative aiming to implement a model for integrated healthcare and social services in the Québec City region. Started in 2004, this well documented initiative[1,2] is lead by the region's Agency for Development of Local Health and Social Service Networks. Insights gained through this case should be useful knowledge to health care network authorities in other regions aiming toward more patient centricity and distributed regional distribution.

Key success factors

Concurrently focusing on population centricity and individual centricity the network aims toward maximizing its value contribution to the entire population and each individual. It is their expectations that the network has to satisfy, as much as possible.

It is crucial to gather population expectations and individual expectations, and to validate their legitimacy because they should become the basis for performance assessment.

Taking an overall service trajectory perspective and setting network-wide goals for each process.

Clear goals and objectives should be expressed for each process along the service trajectory for each type of care services. For example, in combatting cancer, the service trajectory includes processes such as prevention, suspicion, diagnostic, treatment, healing, palliative care, terminal care and lifelong monitoring.

Guiding each professional's mind frame toward a patient-centered collaborative stewardship across the multiple network levels. The aim should be to create a patient-centric multi-level collaborative network, involving patients, doctors and field processionals, local teams, regional teams and supra-regional teams. Actors at each level should learn to feel deeply that they are bound by a common stewardship to the health and well being of each patient and the overall population.

Instilling collaborative networking as a core competency mastered by all professionals.

The roles and responsibilities of each actor, care providers as well as managing and support actors, have to be adapted to insure that the development and exploitation of collaborative networking becomes a core competency. Teamwork through the network must become the normal way of working. Generalists must take a responsible attitude relative to the entire service trajectory and the health evolution of each of their patients. Specialists must adopt a network approach with other specialists as well as with first line professionals handling pre and post treatment. Migrating from a loose network of institutions toward an agile service web. There should be a strong drive for moving away from managing organizational silos toward enabling and driving value creation processes.

Value creation processes should seamlessly integrate an elaborate multi-institution network of regional specialized services, involving private and public actors, and allowing the appropriate movement of actors through the network, enabling to create a virtual team for each patient through his service trajectory, focusing on accessibility, continuity and quality. Fostering a synergistic and collaborative interdependency between territorial networks

A regional network is to be subdivided in local territorial networks. Each territorial network should aim to satisfy as best as possible the expectations of its population and its individuals. Each can expect to be provided with the means to fulfill its mission and to be treated equitably. Territorial wars are the pitfall to be avoided, and are the result of a quest for autonomy and the piling of interface problems.

The aim should be to create a synergistic geographical interdependency. Each territorial network needs to have the means for offering excellent proximity front line services adapted to its population. There should be sharing of resources and mutual reinforcement when facing crises and there should be an interdependency for regional and supra regional specializations. Orchestrating the implementation around focused clinical, competency and infrastructure projects

Implementation work has to be activated along two complementary axes. On one axis clinical projects should be developed and implemented, involving early investigation through simulation and pilot projects, followed by wider scope implementation initiatives once potential value has been demonstrated. On the second axis, there should be work toward the development and exploitation of network competencies and network infrastructure. Clinical projects should lead the network transformation. This implies the prioritization and activation of a set of clinical projects covering as best as possible the spectrum of health and social care needs in the region. There should be a strong drive to develop an information/communication infrastructure enabling the networking initiative, focused on real value creation be supporting the actors towards an ever more efficient and synergistic collaborative operation.

Committed leadership and strategic action

It is important to shape and empower the network development leadership organization, involving all key stakeholders in the region. The leadership should be driving into action a set of complementary implementation strategies. For example, these may include a priority clinical project strategy, a local territorial network center launching strategy, an impact evaluation and measure strategy, a change management and mobilization strategy, a university project strategy, and an interdependency realization strategy. There should be regular follow up of projects and feedback to key stakeholders.

Conclusion

Patient centric distributed network approaches show potential to help improve health and social services delivery. It should be clear that such initiatives are complex and must be carefully conceived and prepared from strategic, organizational and operational perspectives. The complexity and scope of the resulting transformations should never be underestimated.

Understanding the success factors described in this paper and taking action toward their realization are key for durable fruitful implementation having long lasting high impact on the health and well being of the population and each of its individuals.

Concerning the Québec region project, only time will permit to verify whether it will be a durable success, a failure, or a mixed result. Subsequent analysis should permit to gain additional learning potentially transferable to other regions.

References

- Le modèle régional d'organisation de services de santé et de services sociaux intégrés: un défi de proximité, d'accessibilité et de continuité - recommandation au ministre de la Santé et des Services sociaux, 30 avril 2004.
- Projet régional d'organisation de services intégrés (volet mise en œuvre) - Manuel d'organisation de projet - MOP version 2,4; adopté au C.A. de l'agence de développement de réseaux locaux de services de santé et de services sociaux de la Capitale nationale le 30 septembre 2004.

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ORIGINAL ARTICLE

An Operating Room Block Allocation Model to Improve Hospital Patient Flow

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One of the dimensions of healthcare quality is the speed of healthcare treatment; higher quality is associated with shorter patient waiting times. However, due to the significant expense of many healthcare resources (e.g., surgical operating theatres), healthcare managers desire keeping these resources highly utilized. The Theory of Swift Even Flow described by Schmenner and Swink (1998)[1] states that high utilization levels and relatively low throughput times can be maintained only when input flows and processing times are consistent. This theory helps explain the natural tension of quickly moving patients through healthcare operations while simultaneously achieving high utilization. Flow in healthcare environments tends to be very uneven due to random patient arrivals (particularly, emergencies) and highly variable medical procedure times. Variability in flow can affect both patient access to care and the degree of effort put forth by health providers to provide high-quality care. Therefore, healthcare administrators are increasingly focussing on better management of patient flows.[2](see, Hejna (2004), for example).

Surgical operating theatres (OTs) present a particularly interesting opportunity for improving patient flow. While variability due to patients requiring emergency surgery cannot be easily managed, as pointed out by Kim et al. (2000)[3], patients requiring elective or scheduled surgeries can be managed by controlling their admission, optimizing surgery scheduling, or rescheduling planned surgeries. In fact, Haraden and Resar (2004)[4] state that the effect of "artificial" variation caused by the personal preferences and beliefs of clinicians far exceeds the natural variability due to random emergency cases and disease. Scheduled surgery patient flow is one common source for this artificial variation to enter hospitals and healthcare systems.

As part of the surgical scheduling process at many hospitals, the total amount of time available for surgery is allocated to the various surgical services (e.g., cardiac, orthopedic, plastic, etc.) with block schedules created for each month. Surgical services then decide the specific time slots allocated to a surgeon each day.

In this paper we use the mathematical optimization approach of goal programming to improve patient flow by improved surgical service block scheduling. To explore the usefulness of the model in a practical environment we compare block schedules derived from our model with actual scheduling practice at the Foothills Medical Centre (FMC) in Calgary, Alberta. We use computer simulation modeling to provide a detailed comparison.

Goal Programming Model

Our base goal programming model is based on the work of Blake and Donald (2002). In that paper, the authors focussed on meeting the desired hourly targets of the surgical services each month. While this is a primary objective of our research as well, we extended Blake and Donald's model by considering a longer planning horizon, scheduling around holidays, and scheduling different length blocks each day. However, our major contribution is to develop a flow objective to smooth the block schedules. Mathematically, our objective function is

$$\text{Minimize } Z = \sum_{j}\sum_{k}\sum_{w} b^{+}_{jkw} + \sum_{j}\sum_{k}\sum_{w} b^{-}_{jkw} \quad (1)$$

where b^+_{jkw} and b^-_{jkw} are the hours over and under the average daily target for each service j on a day of the week k for week w in the planning horizon. These values are determined using the following soft constraint:

$$\sum_i x_{ijkw} d_{ik} - b^+_{jkw} + b^-_{jkw} = HT_j \qquad \text{j, k, w} \quad (2)$$

where HTj is the daily average target for each service j. The variables x_{ijkw} are the decision variables assigning the number of blocks of type i (regular or extended hours), for surgical service j on day k of week w. Our model then first achieves the desired hourly service targets over a 4-week planning period and then minimizes the deviations from the average hourly service target.

Results

To test the performance of our model in a practical setting we used data from the FMC and built a simulation model of the scheduled surgery and hospitalization process. Data were used to fit mathematical distribution functions for surgery and patient length of stay times for all services. These functions were then used in the simulation model and run for 10 years with repeating schedules from our flow model and actual scheduling practice at FMC.

Figure 1 shows the resulting number of surgical cases and patients in the hospital for the orthopedic surgical service (other services tested show essentially the same result). For surgical cases, the variability is much smaller for our flow model than for current scheduling practice. Note that for the actual schedule the number of days where there are 17 or more surgeries or 6 or fewer is much larger than for our flow model. Therefore, it is clear our model does smooth the number of patients coming out of surgery. (For all tested services, statistical analyses showed significantly lower variability in surgical cases). This should lead to less congestion in post-surgical care units including intensive care and wards leading to better patient flow. The value of a less variable patient flows into intensive care is well discussed in Kim et al. (2000).[3]

However, for the overall number of patients in the hospital there is no apparent difference in the variability of our model compared to actual scheduling practice. In essence, the long length of stay acts as an aggregating mechanism for the variable batch sizes of surgical patients and creates a "smoothing" effect. In addition, the weekends and holidays act to "flush out" the system since no elective surgeries are scheduled on those days. Therefore, on the surface, it appears that the goal programming scheduling leads to smoother output of surgery patients, but makes little difference to overall patient volumes in the hospital.

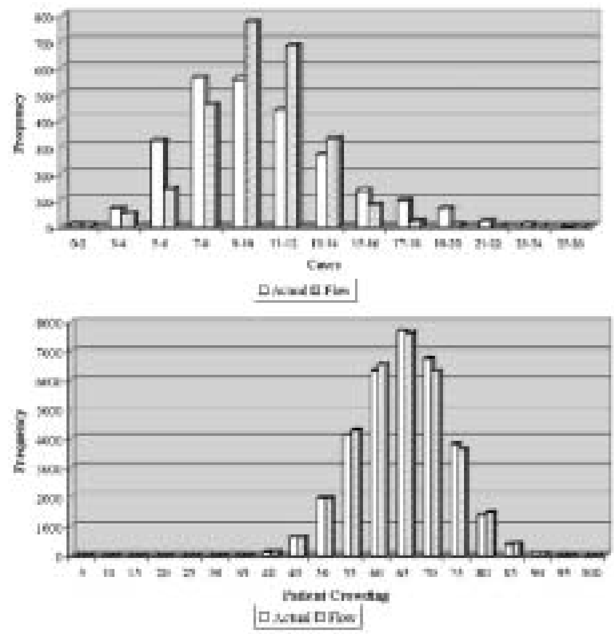

FIGURE 1. Surgical Cases and Crowding for Orthopedic Patients

Conclusions

A positive result of our goal programming model was its ability to reduce the variability of surgical patients and still meet the desired target hours of all surgical services. But, the previous analysis shows that hospital crowding levels may not be improved by advanced scheduling methods. However, one aspect the previous analysis did not incorporate is the interaction between the schedule and length of stay. As with previous OT hospital analyses we assumed the length of stay was independent of the schedule. In fact, a smoother surgery schedule may lead to shorter lengths of stay since congestion in the post surgery processes should be reduced. Less variable patient volumes going into Intensive Care Units (ICUs) and the service wards should lead to less patient waiting as well as higher service quality. One plan for future research is to model the post surgery processes in more detail to show better the value of smoother patient flows.

References

1. Schmenner,R.W, Swink, M. L. On theory in operations management. Journal of Operations Management 1998: 17: 97-113.
2. Hejna,W.J. Five Critical Strategies for Achieving Operational Efficiency. Journal of Healthcare Management 2004; 20 (September/October), 289-92.
3. Kim, S.-C., Horowitz, I., Young, K. K. et al. Flexible Bed Allocation and Performance in the Intensive Care Unit. Journal of Operations Management 2000; 18: 427-43.
4. Haraden, C, Resar, R. Patient flow in hospitals. Frontiers of Health Services Management 2004;20 :3-15.

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ORIGINAL ARTICLE

Seven Rules for Modeling Health Care Systems

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There is much interest in problems concerning how to deliver health care safely, efficiently and effectively. This involves, among other things, managing the delivery system so that it works smoothly, allocating resources such as personnel, beds and equipment efficiently, delivering services at the lowest cost and providing high quality, effective care.[1] However, it is not clear what system designs will achieve these goals. The approach taken by systems engineers and operations researchers, which will collectively be called "modelers," is to build a model of the system that health care administrators can use to predict how the system will respond to proposed modifications, thus allowing the most effective alternatives to be chosen. Many models have been developed for health care systems.[2]

In order to realize the full benefits of the modeling process, the model must be fully implemented and used by decision makers. This requires that managers develop trust in the models so they will feel comfortable using them to evaluate alternative decisions. Ideally, models should be implemented as part of the information system so they can be updated and used routinely by managers.

The process of developing health care system models requires health system managers and care givers to collaborate with modelers. This process can be difficult because these two groups have very different cultures and values. This paper discusses some lessons learned in modeling projects at medium size hospitals. The lessons, which are presented as a series of rules, are presented from the perspective of the modeler and are intended to help health care delivery system modelers develop more effective models.

Rule 1: Health care managers aren't interested in modeling methodology.

Modeling methodology is the mathematical, statistical and other techniques that are used to represent and manipulate the model. To a model developer, it is important whether a model is a mathematical queuing model or a simulation model or an optimization model. But, health care managers, are mainly concerned with whether the model can provide useful solutions to their decision problems. Health care managers deal with problems every day, and most of these problems need immediate attention. Rather than discussing the types of models that can be used, modelers should devote that time to listening to the manager's description of the system and the problems, and asking questions to enhance their understanding.

Rule 2: Data is a limiting factor.

Health care providers keep large amounts of data, but most of the data are collected for medical and legal purposes, not to measure process details for system modeling. For example, in an emergency department, patient arrival times and the times of their first encounter with a physician are recorded in order to determine their waiting time before treatment, but the durations of each physician encounter, which are needed to model the care delivery processes, are not normally recorded. Other problems with data include:

Missing data - Care givers were busy providing care and could not record data.

Incorrect data - Recorded data is incorrect because persons collecting the data were not trained sufficiently.

Data not available - Data is stored on a system or in a format that makes it difficult or impossible to access.

Insufficient data - Data is available but sample sizes are too small to make accurate estimates of parameters.

Data is not well defined - Is the arrival time the moment when the patient enters the door or the moment when the triage nurse encounters the patient?

Data is expensive to collect and maintain, especially if it is collected manually. New information systems should be designed to collect data on work processes automatically using RFID, barcodes and similar technology to automate and simplify this task.

3. You must understand the health care system.
Health care systems are not just manufacturing systems with untreated patients as "raw materials" and treated patients as "finished products". These systems have unique characteristics not present in manufacturing or other model genres. Medical issues are a necessary part of the model. Administrators, many of whom are MDs, want to answer questions such as: How will a change in the epidemiology of the area affect the hospital, or how will operations be affected if the provider starts offering a new service to patients with certain diagnoses? These and other questions require that the medical processes be included explicitly in the model along with the workflow processes.

4. You should model the health care work processes.
Some simulation models of health care systems attempt to follow the physical movement of patients and care givers through the system, ignoring other processes such as consultations with family and other care givers, searching for data, documentation and time spent reviewing and interpreting data. The health care system focuses on the patient, but the model should focus on the work processes. Work processes and the resources required to provide diagnosis and treatment are determined by the patient's diagnosis and other characteristics, so the model must include this relationship. Work processes in health care are very different from those of other systems. For example, care givers make decisions based upon current priorities and are often preempted when a higher priority patient presents.

5. The model should include a financial component.
Health care administrators must evaluate trade-offs between the quality of care and the cost of providing that care. Administrators are also concerned with risk management, i.e., how much variation in financial outcomes can be expected and how effective are various plans to mitigate the risk? To perform these evaluations, the model must provide estimates of financial performance in addition to quality of care measures. For some models, these could be simple computations of expected cost per day or per patient, or they could be based upon an implementation of the provider's reimbursement schedule.

6. The model should include data management processes.
Much of the work in health care involves gathering, storing, retrieving and sharing data. Many proposals to improve or reform the health care system include implementing new information systems that integrate providers' information and improve efficiency of data collection and retrieval. To evaluate the value of these new systems, models should include the activities associated with data management. These activities involve such things as patient records retrieval and review, care documentation, and transcription. The activities should also include time for the interpretation of non-standard data. EMRs will standardize some data, requiring care givers to use the same terminology and formats and reducing the time to review that data. Models that include the data management activities can be used to evaluate proposed changes in the information system and workflow processes that promise to increase the efficiency of the health care processes.

7. The model must be built quickly.
The health care system and the problems administrators must deal with are constantly changing. Administrators move to different positions or providers; staff who are familiar with the model change jobs; new facilities, processes and policies are implemented; data are no longer current; and the epidemiology of the area changes. If the model is not developed within a few months, chances are high that it will not be valid for the current system or it will no longer be a priority for management. Available tools for rapid modeling of health care systems are not generally available. These tools should include pre-built component such as arrival processes, laboratory and imaging process models, scheduling models and reimbursement models, depending upon the type of model being developed. With such tools, model building would involve assembling and configuring activities, rather than program coding.

Conclusion
Large providers and government agencies are showing a growing interest in supporting model development in health care. These models have the potential to greatly improve the efficiency and effectiveness of care

delivery. It is hoped that these seven rules will increase the efficiency and effectiveness of the modeling process and lead to models that are implemented and used routinely in the design and management of health care systems.

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References

1. Reid, P. P., W. D. Compton, J. H. Grossman, G. Fanjiang, eds. 2005. Building a Better Delivery System: A New Engineering/Health Care Partnership. Washington, DC: National Academies Press.
2. Brandeau, M. L., F. Sainfort, W. P. Pierskalla, eds. 2004. Operations Research and Health Care: A Handbook of Methods and Applications. International Series in Operations Research and Management Science Vol. 70. Boston, Mass.: Kluwer Academic Publishers.

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ORIGINAL ARTICLE

Policy Analysis Using Patient Flow Simulations: Conceptual Framework and Study Design

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Summary
How do we know that innovations in healthcare delivery would work? In this paper, we discuss the idea of applying the methodology of group-randomized intervention studies to evaluation of surgical care policies using data from simulation experiments. We argue that a new interdisciplinary framework, which links health services research, operations research, and computer sciences, is required. Specifically, the methodological rigor of evaluative studies should be applied to the analysis of simulation experiments.[1] In turn, the evaluation of policy initiatives should include the simulation of health-system operations.[2] We introduce the framework and study design to evaluate methods for improving the peri-operative process with the use of patient flow simulations.

Policy analysis using simulations
Intervention studies evaluate policy changes implemented in hospitals, wards or services by comparing clusters of individuals. Therefore, clusters of individuals rather than individuals themselves are randomized to different intervention groups.[1]

Computer simulation is an operations research technique to evaluate a system's performance.[3] The underlying premise is that a collective experience of individual simulated paths through the system is the result of the system's operations and can be used to represent care delivery to a virtual cohort of patients. Modeling patient flow in health care is considered a powerful approach to assessing the likely response of a health system to changes in organization, management and policy.[4,5]

Objectives
The aim of the proposed study is to evaluate methods for improving surgical patient flow that have been suggested for the following fourteen peri-operative activities:

Scheduling outpatient clinic appointments;
Pre-surgical screening;
Scheduling anesthesiology consultations;
Managing access to elective surgery;
Scheduling elective patients for surgery;
Prioritizing patients for hospital admission;
Re-scheduling cancellations of scheduled surgeries;
Managing operating room time utilization;
Managing direct admissions;
Managing operating room utilization;
Sequencing patients;
Managing post-anesthesia care;
Discharge planning before surgery; and
Managing post-operative care.

Simulation analyses will be performed for each of the activities separately, with intervention groups defined by the management and policy alternatives, see Table 1.

The specific objectives are:

1) To compare the proportion of patients experiencing index outcome in simulated intervention groups to the proportion of patients with index outcome in the control group for each peri-operative activity.

2) To compare the proportion of hospitals demonstrating benchmark performance in simulated intervention groups to the proportion of hospitals with benchmark performance in the control group for each of the 14 peri-operative activities.

TABLE 1. Management and policy alternatives for improving patient flow

activity/intervention	*indicator variable**
Scheduling outpatient clinic appointment	
• specialist-specific appointment lists	A10
• pooling all referrals on one appointment list	A11
• offering choice between same-week and future appointment with preferred surgeon	A12
Pre-surgical screening, impact on cancellations after admission	
• some elective patients are assessed after admission	A30
• all elective patients are screened through pre-admission clinic	A31
• all scheduled patients are medically optimized before admission for surgery	A32
• all patients and their families are educated about the procedure and care	A33
Scheduling anesthesiology consultation	
• anesthesiologist-specific consultation lists	A40
• consultation with available anesthesiologist, not the anesthesia provider during surgery	A41
Managing access to elective surgery	
• multiple wait lists of individual surgeons	A50
• centralized wait list by procedure	A51
• unlimited surgical wait lists	A60
• regulated surgical wait lists with redistribution of cases	A61
• non-monitored surgical wait lists	A70
• monitored surgical wait lists	A71
Scheduling patients for surgery, impact on non-clinical cancellations	
• current booking of admission dates	A80
• advanced booking of admission dates	A81
• the OR schedule confirmed with surgeon's office at least one day prior to surgery	A82
Scheduling patients for surgery, impact on time to admission	
• short notice pool of pre-screened patients to fill OR time that unexpectedly becomes available	A91
Scheduling patients for surgery, impact on clinical cancellations	
• profiling case based on type of procedure	A100
• the surgeon's office provides all information to develop OR slate	A101
Prioritizing patients for hospital admissions	
• priority groups	A110
• continuous urgency rating score	A111
• dynamic prioritization (urgency upgrade, increasing priority with time spent)	A112
Re-scheduling cancellations of scheduled cases, impact on time to admission	
• scheduling cancelled and postponed surgeries for weekend	A121
Re-scheduling cancellations of scheduled cases, impact on time to readmission	
• increasing priority upon reinstating on wait list	A131
Managing direct admissions	
• network of hospitals to pool urgent patients for expedited admission	A141
Managing operating room utilization, idle time	
• general-administration operating rooms	A150
• specialty-dedicated operating rooms	A151
Managing operating room utilization, cancellations by hospital	
• dedicated emergency slots within daily planned schedule	A160
• dedicated emergency operating rooms	A161
Sequencing patients	
• outpatient cases earlier, inpatient case later	A170
• similar cases grouped by surgeon, priority, procedure	A171
• major cases earlier, minor cases later	A172
• longer cases earlier to avoid overtime	A173
• shorter cases earlier to reduce variability in procedure time	A174
Managing post-anesthesia care, cancellations for no ICU bed	
• holding patients in PACU in order to ensure a ICU bed	A181
Managing post-anesthesia care, cancellations for insufficient staff	
• adjusting staffing pattern to fluctuations in case-mix	A191
Discharge planning before surgery	
• post-operative services are identified before surgery	A200
• all elective scheduled patients undergo discharge planning before admission	A201
Managing post-operative care, impact on cancellation for no ICU bed	
• diversion to different hospital if critical care bed unavailable	A211

*The indicator variables will be used for developing regression models.

Approach

Our approach has three premises:

1) The interventions have been designed to improve patient outcomes within hospital surgical services;

2) In one hospital, patients may influence each other because of prioritization and competition for common resources; and

3) Evaluation of management and policy interventions that are implemented at an organizational level require comparing clusters of individuals.

We will employ a cluster randomization trial design, which allocates clusters of patients to peri-operative intervention groups.[6] Each cluster will represent a simulation experiment performed in a hypothetical hospital under conditions specified by the intervention. The clusters will be randomly assigned to an intervention group or to a control group.

Changes in patient flow will be measured in terms of the proportion of patients experiencing outcomes relevant to each activity and the proportion of hospitals demonstrating benchmark performance. Fig. 1 illustrates the approach by showing the distribution of experiments by the number of patients waiting during weeks with no appointment available in a simulation study of two scheduling methods.[7] All evaluations will be done at the patient and group levels using patient-level data.

Methods

Analyses of proportions will be performed separately for each outcome using formulas that have been adjusted to allow for dependence between observations within the same cluster.[8] For group-level analysis, the Pearson chi-square statistic, adjusted for the clustering design effect, will be used to compare the proportions from each intervention group with corresponding "control" proportions to determine if there is a significant change in the proportion of those receiving the service after the implementation of the intervention. For patient-level analyses, the intraclass correlation coefficient (ICC) will be estimated from the study data to adjust for dependence between observations.

Regression methods for group-level comparisons will include generalized linear models for rates and proportions. Generalized estimating equations (GEE) will be used to fit regression models to determine the effect of the interventions on patient flow.[9] The GEE method treats dependence between individual observations as a nuisance parameter and corrects estimates for clustering.

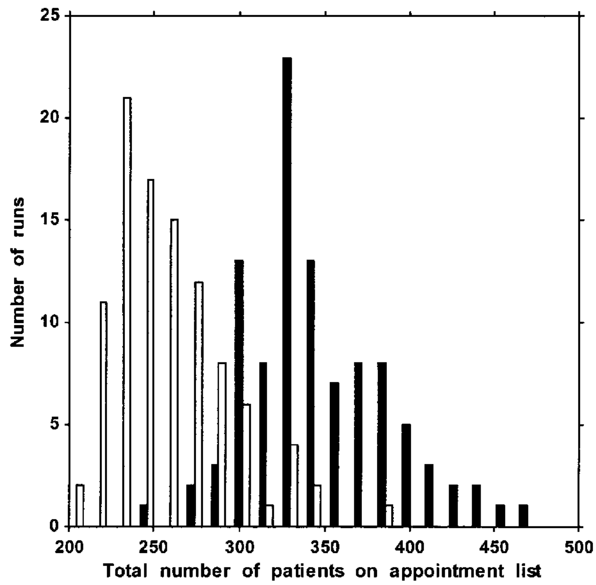

FIGURE 1. Group-level comparison using the distribution of experiments by the number of patients waiting for appointment during weeks with no appointments available in intervention (black) and control (white) groups. (Details of the analysis are described in Vasilakis, Sobolev, Kuramoto and Levy. A simulation study of scheduling clinic appointments in surgical care: individual-surgeon versus pooled lists. JORS 2005)

Research plan

A study population will comprise all simulated referrals to surgeons in one specialty in a given hospital. Clusters of patients is generated by simulation experiments. Patient characteristics - age, sex, urgency, procedure, hospital, and co-morbidities - will be randomly assigned within each cluster. Equal numbers of clusters will be simulated for each intervention group. A random combination of values of confounding variables will be assigned to each cluster before randomization to an intervention group. These variables will represent characteristics of additional (i.e., not studied in a particular evaluation) peri-operative activities, and hospital settings.

To ensure a sufficient sample size for group-level comparisons, the number of experiments (clusters) per intervention group will be chosen to be adequate for testing each hypothesis. For multivariate regression analysis of group-level data with a set of 20 confounding variables and one indicator variable for the two intervention groups, we will need 420 experiments divided between the two groups allowing for 20 observations per independent variable.

In the previous analysis of waiting times for coronary bypass surgery we found that cluster level attributes had a common influence over all individuals in that cluster making them more similar as compared to individuals from another cluster.[10] In this case, the ICC was 0.18 for time to surgery and 0.07 for surgery within target time across clusters defined by hospital-period interaction.

For regression analysis of individual patient data, we estimate that we will need 206 experiments per intervention group with 400 subjects in each cluster to detect a difference of one week in the average time between the peri-operative activities (ICC=0.20), with a 90% power and a two-tailed false positive rate, alpha, of 5%. To detect the anticipated effect size of 5% in proportions, we will need 98 experiments per intervention group with 400 subjects in each experiment (ICC=0.10), with a 90% power and alpha of 5%. Therefore, 210 experiments per intervention group will be adequate both for group-level and individual-level comparisons.

Specific hypotheses

Hypothesis 1. Clinic-appointment interventions improve surgical patient flow as measured by the proportion of appointments within target time (patient-level evaluation [P]), and the proportion of hospitals with less than half of extended waits for appointment (longer than target access time) (group-level evaluation [G]).

Hypothesis 2. Pre-surgical screening interventions improve surgical patient flow as measured by the proportion of cancelled surgeries (P), and the proportion of hospitals with less than one tenth of surgeries cancelled due to patient-related reasons (G).

Hypothesis 3. Anesthesiology-consultation interventions improve surgical patient flow as measured by the proportion of consultations within target time (P), and the proportion of hospitals with less than half of delayed consultations (G).

Hypothesis 4. Access-management interventions improve surgical patient flow as measured by the probabilities of admission within certain times of wait-list registration (P), and the proportion of hospitals with less than half of extended waits (longer than target access time) for admission (G).

Hypothesis 5A. Scheduling-surgery interventions improve surgical patient flow as measured by the proportion of scheduled cases cancelled on the day of surgery or within 48 hours by patient or hospital for non-clinical reasons (P), and the proportion of hospitals with less than one tenth of surgeries cancelled due to non-clinical reasons (G).

Hypothesis 5B. Scheduling-surgery interventions improve surgical patient flow as measured by the probabilities of admission within certain times of wait-list registration (P), and the proportion of hospitals with less than half of extended waits (longer than target access time) for admission (G).

Hypothesis 5C. Scheduling surgery interventions improves surgical patient flow as measured by the proportion of scheduled cases cancelled on the day of surgery or within 48 hours by patient or hospital for clinical reasons (P), and the proportion of hospitals with less than one tenth of surgeries cancelled for clinical reasons (G).

Hypothesis 6. Patient-prioritizing interventions improve surgical patient flow as measured by the time-dependent weekly rates of: a) symptom worsening; b) urgency upgrade; c) pre-operative death; d) becoming unsuitable for surgery; and e) unexpected emergency admission before index admission (P), and the proportion of hospitals with benchmark rates of the adverse events (G).

Hypothesis 7A. Re-scheduling interventions improve surgical patient flow as measured by probabilities of admission within certain times of wait-list registration (P), and the proportion of hospitals with less than half of extended waits (longer than target access time) for admission (G).

Hypothesis 7B. Increasing priority for cancelled cases improves surgical patient flow as measured by probabilities of re-admission within certain times of cancellation during hospital admission (P), and the proportion of hospitals with less than half of extended waits (longer than week since cancellations) for re-admission (G).

Hypothesis 8. Direct-admission interventions improve surgical patient flow as measured by the proportion of surgeries in the week of direct admission to hospital (P), and the proportion of hospitals with more than half of surgeries within a week of direct admission (G).

Hypothesis 9. OR utilization interventions improve surgical patient flow as measured by the proportion of surgeries performed on days that are less than fully booked (P), and the proportion of hospitals with OR not fully booked more than 10% of the time (G).

Hypothesis 10. ORs dedicated to emergency cases improve surgical patient flow as measured by the proportion of scheduled cases cancelled on the day of surgery by the hospital for non-clinical reasons (P), and the proportion of hospitals with less than one tenth of surgeries cancelled for non-clinical reasons (G).

Hypothesis 11. Case-sequencing improves surgical patient flow as measured by the proportion of scheduled cases cancelled on the day of surgery by the hospital for insufficient time (P), and the proportion of hospitals with less than one tenth of surgeries cancelled for insufficient time (G).

Hypothesis 12A. Post-anesthesia care interventions improve surgical patient flow as measured by the proportion of scheduled cases cancelled on the day of surgery because of ICU bed unavailability (P), and the proportion of hospitals with less than one tenth of surgeries cancelled for no ICU bed available (G).

Hypothesis 12B. Adjusting staffing levels to fluctuations in case-mix improves surgical patient flow as measured by the proportion of scheduled cases cancelled on the day of surgery or within 48 hours by the hospital for insufficient nursing and post-operative staff (P), and the proportion of hospitals with less than one tenth of surgeries cancelled for insufficient staff (G).

Hypothesis 13. Discharge-planning intervention improves surgical patient flow as measured by the proportion of patients not discharged in a timely fashion due to no home care arranged, no rehabilitation service available, or no long-term care bed available (P), and the proportion of hospitals with less than half of extended post-operative length of stay (G).

Hypothesis 14. Post-operative care improves surgical patient flow as measured by the proportion of cases cancelled on the day of surgery by the hospital for no ICU bed available (P), and the proportion of hospitals with less than one tenth of surgeries cancelled for non-clinical reasons (G).

Anticipated Findings

By evaluating data of simulation experiments we will determine the effectiveness of policy and management alternatives in improving peri-operative process. We will use several outcomes measures, as a specific policy may have differential impact on different stages of patient flow. Hospital-level comparisons will document how likely it would be that hospitals improve patient flow after adopting the proposed methods. Individual-level comparisons will document likely results of undergoing services in a hospital using these methods.

The evaluation of management and policy initiatives based on simulation experiments provides an opportunity to generate invaluable information about suggested methods for improving surgical patient flow. Thus, the knowledge learned from this evaluation will inform peri-operative program development aimed at changing surgical services delivery.

References

1. Ukoumunne OC, Gulliford MC, Chinn S, Sterne JA, Burney PG, Donner A. Methods in health service research. Evaluation of health interventions at area and organisation level. BMJ 1999; 319(:376-379.
2. Butler TW, Reeves GR, Karwan KR, Sweigart JR. Assessing the impact of patient care policies using simulation analysis. J Soc Health Syst 1992; 3:38-53.
3. Jun JB, Jacobson SH, Swisher JR. Application of discrete-event simulation in health care clinics: a survey. J Oper Res Soc 1999; 50:109-23.
4. Fone D, Hollinghurst S, Temple M, Round A, Lester N, Weightman A et al. Systematic review of the use and value of computer simulation modelling in population health and health care delivery. J Public Health Med 2003; 25:325-35.
5. Harper PR, Shahani A. Modelling for the planning and management of bed capacities in hospitals. J Oper Res Soc 2002; 53:11-8.
6. Lesaffre E, Verbeke G. Clinical trials and intervention studies. In: Everitt B, Howell D, editors. Encyclopedia of Statistics in Behavioral Science. Second Edition ed. Wiley; 2005.
7. Vasilakis C, Sobolev BG, Levy AR, Boyko S. An asynchronous event-driven model of surgical process scheduling. 17th Triennial Conference of the International Federation of Operational Research Societies; 05 Jul 11; Honolulu, Hawaii, USA. INFORMS, 2005
8. Donner A, Klar N. Cluster randomization trials in epidemiology: theory and application. Journal of Statistical Planning and Inference 1994; 42:37-56.
9. Zeger SL, Kung-Yee L, Albert PS. Models for Longitudinal Data: A Generalized Estimating Equation Approach. Biometrics 1988; 44:1049-60.
10. Sobolev B, Levy AL, Hayden RH, Kuramoto L. Does wait-list size at registration influence time to surgery? Analysis of a population-based cardiac surgery registry. Health Serv Res 2005; in press.

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ORIGINAL ARTICLE

An Outpatient Segmentation Model: Estimation of Stakeholder Costs

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Summary
This research describes a constraint-based heuristic model of capacity segmentation for outpatient facilities used to estimate the effect of segmentation constraints on stakeholders.

Growth of free-standing ambulatory surgery centres has been dramatic in recent years with institutions being urged by governments and insurers to segment inpatients (IP) and outpatients (OP) to reduce costs and improve services. Critics of segmentation argue it is a false economy to separate inpatients and outpatients since pooling of patients in large IP facilities offers economies of scale and opportunities for parallel processing, not to mention elimination of infrastructure. We implemented a constraint-based heuristic model of capacity segmentation for OP facilities and used it to estimate the effect of segmentation on stakeholders.

Methods
With permission of the institution that collected the data, we modeled surgical schedules using historical case records of 60,643 surgeries performed over 2,260 days at a large academic medical center. Data were collected using a previously described computerized system.[1] Variables in the data set included total procedure time, date, time and location of the surgeries, and the surgical procedures classified by Current Procedural Terminology (CPT).

To evaluate the effects of segmentation, we studied schedule outcomes described in more detail elsewhere.[2,3] These schedule outcomes included budgeted time (the time available in which the institution purchases skilled labour and expects to produce surgical services), patient wait time (time the patient waits but does not receive surgical services), surgical time (the demand for surgical services), idle time (scheduled time that does not produce surgical services), total time (the sum of budgeted plus overtime), capacity (the number of operating rooms multiplied by the time available to supply surgical services), and overtime (time that the institution produces services at premium cost). The impact of segmentation was evaluated by estimating the cost of schedule outcomes to stakeholders.

To segment outpatients, we used a modified newsvendor model[4,5] implemented in Allegro Common LISP using best-fit decreasing (BFD) and best-fit increasing (BFI) rescheduling heuristics.6. OP segmentation was accomplished using an ordered list with constrained enumeration to minimize total stakeholder costs (TSC) of daily surgical operations. Historical surgeries were scheduled into 18 operating rooms parsed appropriately into inpatient and outpatient facilities to minimize TSC of the combined facility (CF). BFD heuristics were used to emulate scheduling policies that minimized institutional costs while BFI rescheduling heuristics were used to mimic policies that favored convenience for OP and surgeons.

Stakeholder costs were derived from schedule outcomes. Wait time (WT) was valued at 15% and overtime at 200% of budgeted time. Institutional costs (IC) were calculated as the sum of budgeted time plus overtime. TSC was calculated as the sum of IC plus patient costs (15% of the sum of WT plus surgical time). IC and WT were used as surrogate measures of the effects of seg-

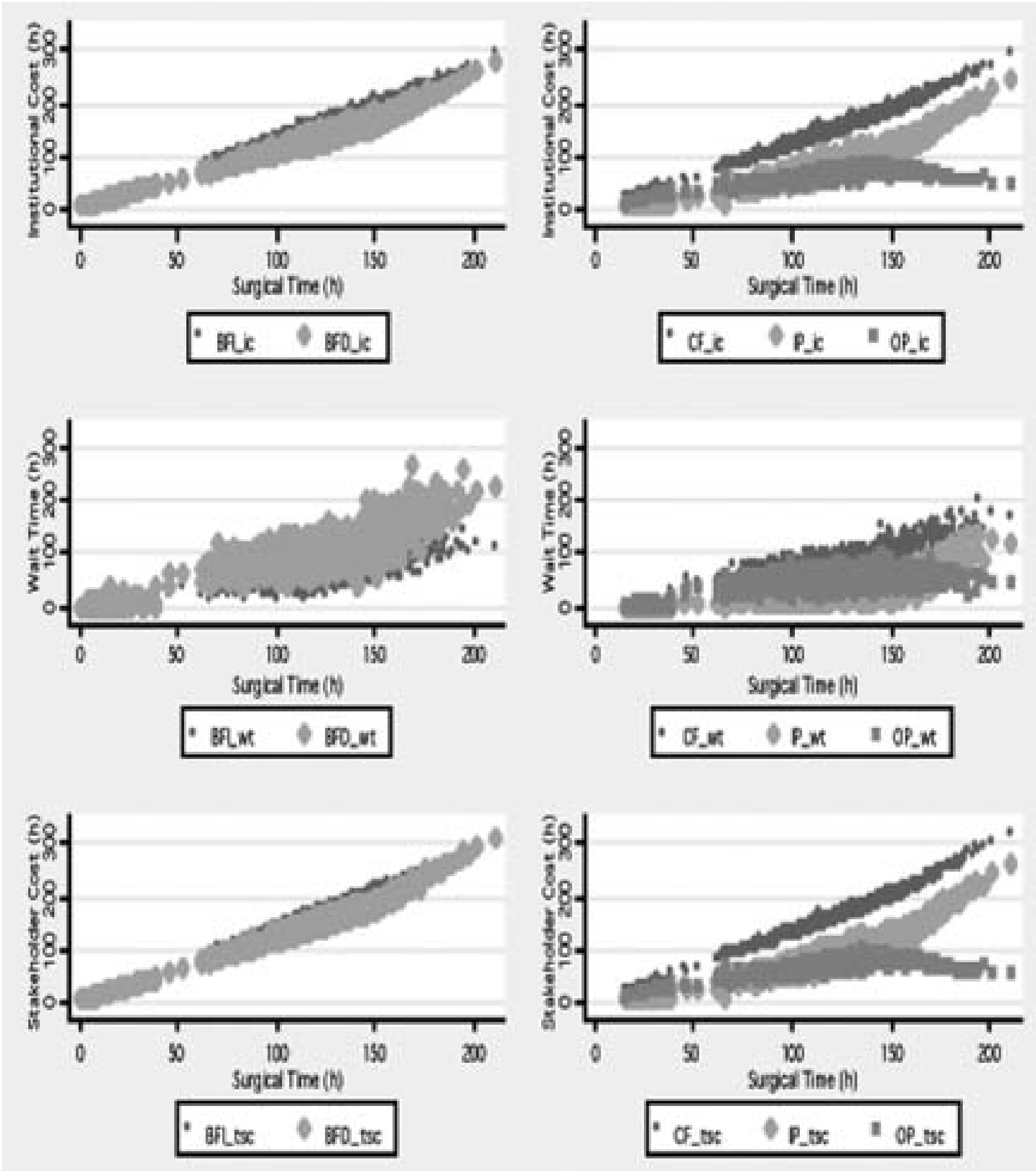

FIGURE 1. Six panels illustrate surgical time (demand) versus institution costs (IC), patient wait time (WT), and total stakeholder costs (TSC). IC is the sum of budgeted time and 2 times the overtime. TSC is the sum of IC plus 0.15 times the sum of surgical time and WT. The left panel compares schedules optimized Best-Fit Decreasing (BFD) to optimize institutional costs and Best-Fit-Increasing (BFI) to minimize patient WT. The right panel compares combined facility (CF) schedules optimized to TSC to inpatient (IP) and outpatient (OP) facilities individually. Weekdays, weekends, and holiday days were segmented, n = 2,260 days.

mentation on institutional and patient stakeholders respectively. Stakeholder costs were aggregated on a daily basis and summarized using linear regression. Relative rates of stakeholder costs (%) were reported with respect to surgical demand. CF schedules were compared with unsegmented facilities rescheduled using standard BFD and BFI scheduling policies.

To achieve our segmentation model, we removed scheduling constraints due to order of procedures, overlap/non-overlap of surgeries by a surgeon, block scheduling, use of overtime, and turnover times to make our analyses technically and intellectually feasible. In doing so, we attempted to maintain a breadth of surgical experience, all the various surgical subsets and subspecialties, and the variability and procedural diversity of real data[7] while at the same time minimizing the potential for biasing our results.

Results

Our database contained 3,424 different CPT codes performed by 270 surgeons and 152 anesthesiologists over 2,260 days. Surgical procedure durations ranged 5-1440 min. The mean age of patients was 48.5 ± 18.4 yr (mean ± SD) with 50% males and 50% females. Of all surgical procedures, 61.6% were associated with general anesthesia, 12.4% local, 18.9% regional, and 7.1% were monitored with sedation.

Institution costs, wait time, and stakeholder costs were plotted with respect to surgical demand (x-axis) and unsegmented (left panel) and segmented (right panel) facilities were compared in Figure 1.

The left panels compare surgical schedules optimized BFD to schedules optimized BFI. The right panels compare CF schedules optimized to TSC with surgeries rescheduled to IP and OP facilities individually.

Institutional costs (IC) were 16% greater and total stakeholder costs (TSC) were 11% greater than unsegmented facilities scheduled BFD. Patient wait times (WT) were 25% less in segmented facilities compared with unsegmented facilities scheduled BFD ($P < 0.00$, $n = 2{,}260$ days).

Conclusion

We implemented a constraint-based heuristic model of OP segmentation. A newsvendor model was used to parse surgical demand and scheduling heuristics were employed to reschedule IP and OP facilities to minimize CF costs. The effects of OP segmentation on stakeholders were estimated using schedule outcomes. IC and TSC were greatest in segmented facilities while patient WT was least in segmented facilities.

We used scheduling heuristics and not a human scheduler to model scheduling policies. In addition, to investigate the segmentation constraint, we removed other constraints from the schedules to reduce confounding influences and potential constraint interactions. A real world schedule would never be assembled without constraints. The interdependence of scheduling constraints and the magnitude and nature of their potential interactions is not known at present. With further research, we anticipate future models will automate schedules using more realistic and complex constraints.

Long wait lists for surgeries have led to recognition in the literature of a need to develop analyses to support evidence-based management of surgical services.[8] Data is of little value without analytical tools to transform data into management knowledge. Operations research and modeling are important because they establish the decision support tools needed to begin measurement and experimentation.[9]

To be useful, complex statistical models must be designed, developed, tested, and realized as mathematical and ultimately as computational models translated into software. Scheduling policies developed from such analyses could then be formulated and tested by management prior to actual implementation in hospitals. These models could then be used to inform surgical scheduling policies and evidence-based management of wait times.

References

1. Bashein, G., Barna, C, A comprehensive computer system for anesthetic record retrieval. Anesth Analg, 1985. 64: 425-31.
2. Strum, D.P. and L.G. Vargas, Evaluation of surgical services using surgical schedule outcomes. Anesth Analg, 2004. 98: S78.
3. Strum, D.P,. Vargas, L.G. Schedule outcomes for evaluating surgical schedules and institutional service outcomes. Submitted to Anesthesiology, 2004:
4. Lippman, S.A., McCardle, K.F. The competitive newsboy. Operations Research, 1997;45:54-65.
5. Strum, D.P., L.G. Vargas, May, J.H. Surgical subspecialty block utilization and capacity planning: a minimal cost analysis model. Anesthesiology 1999;90:1176-85.
6. Kennedy, M.H., Bin-packing, knapsack, and change-constrained approaches to operating room scheduling, in Department of Decision Sciences and Engineering Systems. 1994, Rensselaer Polytechnic Institute: Ann Arbor. p. 205.
7. Strum, D.P., et al., Surgeon and type of anesthesia pre-

dict variability in surgical procedure times. Anesthesiology, 2000;92:1454-66.
8. Zellermeyer, V. Report of the surgical process analysis and improvement expert panel. 2005, Government of Ontario: Toronto. p. 1-70.
9. Walshe, K., Rundall, T.G. Evidence-based management: from theory to practice in health care. Milbank Q, 2001. 79(3): p. 429-57, IV-V.

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ORIGINAL ARTICLE

Comparing Two Methods of Scheduling Outpatient Clinic Appointments Using Simulation Experiments

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In access to elective surgical care (i.e. medically necessary but not emergency), the total length of time that patients have to wait for surgery after being referred by their primary care physician consists of the time from referral to appointment with surgeon and the time from appointment to surgery.[1] Time to appointment depends on the number of referrals, the availability of surgeons for appointments, and the method of scheduling appointments.[2]

In care services where surgeons maintain individual appointment lists the availability of referral surgeon influences time to appointment. Appointment is scheduled when the referral surgeon is available for clinic appointments. Surgery schedule, teaching, involvement with research and vacation periods may delay appointments with surgeons. As a result, time to appointment may vary greatly between patients.[3]

Pooling referrals on one appointment list and scheduling appointments with the first available, not referral, surgeon was recommended as a method of reducing time to appointment. It has been argued that by eliminating periods when appointment with particular surgeon cannot be scheduled, the impact of schedules of individual surgeon on the time to appointment can be reduced.[4] It has also been argued that pooling referrals reduces the uneven distribution of patients over individual waiting lists[5] which may contribute to variation in waiting times as well.[6]

Little is known however, on how the pooled-lists method affects time to appointment in a service where surgeons engage in multiple activities. It is also not known how the method may impact time between appointment and surgery as more patients will be seen and registered for surgery per time unit. Additional uncertainty of the impact the pooled-lists method may have on waiting times relates to the prioritization of patients on appointment and surgical wait lists.

The purpose of this study was to compare, by means of simulations, two methods for scheduling outpatient clinic appointments in a surgical service where the availability of surgeons for appointments depends on other activities within clinical practice. The methods we compared were individual-surgeon appointment lists and scheduling appointments with referral surgeon (method 1), and pooled appointment lists and scheduling appointments with the first available, not referral, surgeon (method 2).

Methods

We considered a surgical care service in which three surgeons have admitting rights to a single hospital. We based our model on the description of cardiac surgery service at a tertiary hospital in British Columbia (BC), Canada, one of the four hospitals delivering all adult open-heart surgeries to four million residents of BC.[7] The hospital provides the surgeons with an outpatient clinic and a dedicated operating room (OR). Use of clinic and OR time is managed through the periodic allocation of clinic and OR slots to surgeons.[8]

The three surgeons coordinate their weekly duties so that one is on-call and performs some operations (on-call duty), one is at clinic and assesses patients from appointment list (office duty), and the third surgeon performs the majority of operations (OR duty).

When a surgeon is on vacation, the two remaining surgeons alternate their OR and on-call duties, leaving the office duty unfilled and resulting in periods when no clinic appointments are scheduled. The duty rotation and vacation schedule of surgeons is planned for 18 weeks in advance.

We abstracted the surgical care delivery as an event-driven reactive system involving multiple concurrent processes.[9] In total, we modeled five care processes in outpatient clinic, eight in hospital and two supporting processes. Statecharts visual formalism was employed to model the care processes.[10] By using Statecharts we defined the behaviour of each modeled process by the set of allowed sequences of events, conditions, actions and temporal logic associated with the events and conditions.

We constructed a discrete-event simulation model[11] in which we modeled the progress of individual patients in surgical service as a series of updates in patient records in reaction to events generated by care processes in asynchronous fashion. We included the elective, urgent and emergency care pathways that are common in many surgical services.[7]

Two versions of the simulation model described above were developed to account for the differences between the two methods. The outcomes used were number of appointments and operations, and times from referral to appointment and from appointment to surgery. We ran each version of the model 100 times with different random number series to estimate the variability in outcomes. Each run was 108 weeks long. Model parameters were set to correspond to the workload and capacities of the cardiac surgery service in BC mentioned above.

The number of appointments (operations) within pre-defined time frames was compared by the ratio of the total number of appointments (operations) under method 2 to the total number of appointments (operations) under method 1. This standardized access ratio (SAR) is similar to the standardized mortality ratio used in epidemiology.[12] For appointments, the time frame was 12 weeks as virtually all appointments occurred by then. For operations, it was 52 weeks as the majority were done within this time.

We also compared the odds of appointment within six weeks for method 2 over method 1.[13] This time frame was chosen because the combination of duty rotation and vacation schedule limited each surgeon to assessing patients in the clinic once every six weeks. Finally, we compared the odds of undergoing surgery within 18 weeks of appointment for the two methods by also using the odds ratios. The 18-week time frame was chosen to represent the cycle of clinic and OR slot allocation to surgeons.

TABLE 1. The impact of pooled-lists policy on access to appointment and time to surgery as measured by the standardized access ratios and the odds ratios.

	SAR (95% CI)†	Odds Ratio (95% CI)§
Appointment		
Priority 1	2.40 (2.32, 2.47)	3.42 (2.87, 4.07)
Priority 2	2.56 (2.53, 2.59)	6.89 (6.60, 7.19)
Surgery		
Priority 1	0.95 (0.92, 0.98)	1.14 (0.96, 1.36)
Priority 2	0.93 (0.92, 0.94)	0.98 (0.92, 1.05)
Priority 3	0.76 (0.74, 0.77)	0.57 (0.54, 0.59)

Abbreviations: CI = confidence interval; SAR = standardized access ratio; †SAR is the total number of appointments (operations) within 12 weeks (52 weeks) under scheduling method 2 as compared to method 1.

§Odds ratio is the ratio of odds of having appointment (surgery) within six weeks (18 weeks) under scheduling method 2 as compared to method 1.

Results

In total, 200 experiments produced 287144 patient trajectories: 143469 for method 1 and 143675 for method 2. At the end of simulation, 94.4% (method 1) and 96.4% (method 2) of trajectories on elective pathway had progressed through the appointment stage.

We found that, under the pooled-lists method, in the first 12 weeks after referral there were more than twice as many appointments as measured by the SAR 2.40 (95% CI 2.32, 2.47) in priority 1 and 2.56 (95% CI 2.53, 2.59) in priority 2, Table 1. The odds of appointment by week six under method 2 were three times higher for priority 1 patients and 7 times higher for priority 2 as measured by the odds ratio, 3.42 (95% CI 2.87, 4.07) for priority 1 and 6.89 (95% CI 6.60, 7.19) for priority 2. On the other hand, 24% fewer operations were performed in priority 3 patients under the pooled-lists method within the first year after appointment as measured by the SAR = 0.76 (95% CI 0.74, 0.77). The odds of surgery within 18 weeks after appointment in priority 3 were 43% lower for method 2 than method 1, OR = 0.57 (95% CI 0.54, 0.59).

Conclusions

Pooling all referrals to a surgical service on one appointment list and scheduling outpatient clinic appointments with the first available, not referral, surgeon has a differential impact on different segments of the post-referral time and across surgical priority groups. The pooled-lists method shortens time to appointment but increases time to surgery in patients who have been prioritized to non-urgent group.

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References

1. Smith T. Waiting times: monitoring the total postreferral wait. BMJ 1994;30954:593-6.
2. Kipping R, Meredith P, McLeod H, Ham C. Booking patients for hospital care: a progress report. Birmingham: University of Birmingham, Health Services Management Centre; 2000.
3. Ramchandani M, Mirza S, Sharma A, Kirkby G. Pooled cataract waiting lists: views of hospital consultants, general practitioners and patients. J R Soc Med 2002;95:598-600.
4. National Audit Office Wales. NHS waiting times in Wales Volume 2 - Tackling the problem. Report by the National Audit Office Wales on behalf of the Auditor General for Wales. Cardiff, UK: National Audit Office Wales; 2005.
5. Appleby J, Boyle S, Devlin N, et al. Sustaining reductions in waiting times: identifying successful strategies. London: King's Fund; 2003.
6. Katz SJ, Mizgala HF, Welch HG. British Columbia sends patients to Seattle for coronary artery surgery. Bypassing the queue in Canada. JAMA: 1991;266:1108-11.
7. Sobolev B, Levy AL, Hayden RH, Kuramoto L. Does wait-list size at registration influence time to surgery? Analysis of a population-based cardiac surgery registry. Health Serv Res 2005;in press.
8. Blake JT, Donald J. Mount Sinai Hospital uses integer programming to allocate operating room time. Interfaces 2002;32:63-73.
9. Harel D, Pnueli A. On the Development of Reactive Systems. In: Apt KR, editor. Logics and Models of Concurrent Systems. New York: Springer-Verlag; 1985. p. 477-98.
10. Harel D. Statecharts: A visual formalism for complex systems. Sci Comput Program 1987; 8:231-274.
11. Banks J, Carson JSI, Nelson BL. Discrete-event system simulation. 3rd ed. New Jersey: Prentice-Hall; 2001.
12. Finkelstein DM, Muzikansky A, Schoenfeld DA. Comparing survival of a sample to that of a standard population. J Natl Cancer Inst 2003; 95:1434-9.
13. Hosmer D, Lemeshow S. Applied Logistic Regression. New York: John Wiley; 1989.

ORIGINAL ARTICLE

On the Significance of Reducing the Need for Stroke Patients to Visit the Emergency Department

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Abstract:
We studied the care-provider paths followed by 3,946 patients in Quebec in 2001. We showed that the patients flow during the three months preceding discharge from hospital can be represented by a Markov model with memory. This model enables study of four major scenarios to improve health outcomes, workloads and cost efficiency in the overall community-based care delivery system. Based on the field data, we establish that increasing the availability of specialists, family physicians and general practitioners to mitigate the need for ER visits would be an effective strategy for improvement.

A comprehensive policy to support stroke patients needs to incorporate both hospital-based and community-based care delivery processes. The seamless flow of patients through the healthcare providers in such an integrated system is crucial for achieving successful outcomes.[1] Emergency rooms (ER) have a crucial role in this context, since in many cases ER acts as the hospital's "gate keeper", determining if a patient needs to be (re)admitted.[2] In this paper, we establish (based on field data) that mitigating the ER visits of stroke patients improves health outcomes, distribution of workload across the healthcare system as well as associated costs. To this end, we make use of a Markov modeling framework, where the aggregate patient flow information is represented in a compact form through the use of a transition-probability matrix.[3-12] This allows us to investigate the system-wide impact of several plausible scenarios with regards to the delivery of community-based care to stroke patients who are recently discharged from hospital.

Methods

The care providers that patients visit constitute five major categories: family physician (F), general practitioner (G), specialist (S), emergency room (ER), and short-term hospitalization (H). Here, a "family physician" is the general practitioner that the patient has been seeing consistently before the stroke episode. A stochastic process governing the movement of a typical stroke patient from one care-provider to the next is represented by our absorbing Markov model. Our analyses showed that -based on the last two care-providers visited- the probability of a next visit to each of the care-providers can be predicted quite accurately.

Data

The data set in the study was obtained from Regie d'Assurance maladie du Quebec (RAMQ). All care-provider paths following the patients' discharge from Quebec acute-care hospitals in 2001 and their frequencies are determined. While determining the paths, the data obtained from records of fee-for-service billings on visits to care-providers within three months after discharge are used.

TABLE 1: The impact of avoiding ER visits by increasing availability of specialists

Care-Provider	*Cost [12] ($)*	*# of visits Current situation*	*# of visits Scenario #1*	*Reduction (%)*	*# of visits Scenario #4*	*Reduction (%)*
F	40 /visit	4450	4460.16	-0.23	4450.12	0.00
G	40 /visit	1613	1594.44	1.15	1846.03	-14.45
S	55 /visit	4586	4902.17	-6.89	4881.19	-6.44
ER	140 /visit	1341	1070.72	20.16	920.85	31.33
H (7days)	3290 /stay	727	606.51	16.57	568.13	21.85
Sub-path						
H-H		17	15.44	9.20	14.99	11.82
G-H		32	30.54	4.56	34.00	-6.25
S-H		75	76.62	-2.15	79.00	-5.33
ER-H		497	376.95	24.16	334.00	32.80
H-S		145	123.34	14.94	145.62	-0.43
Average Cost ($)		779.1	673.37	13.57	638.21	18.08

Analysis

After validating our Markov model, we conducted scenario analyses so as to develop a solid understanding of the main drivers of health outcomes, workload and costs in the community-based care delivery system to stroke patients. In analyzing health outcomes, we particularly focused on five sub-paths H-H, G-H, S-H, ER-H and H-S, which are associated with significantly higher mortality rates than the overall system average. If the patient were to follow any of these five critical sub-paths the probability of death increases above 10%, while it is around 2% on average. Therefore, mitigating the occurrence of these critical sub-paths would result in better health outcomes in our opinion. Each of the following four scenarios was implemented by altering only the associated portion of the transition-probability matrix. Our findings for the most promising two of these scenarios are summarized in Table 1.

Scenario #1: Channeling 25% of the patients that go to ER during their first visit after discharge from hospital to a specialist. As depicted in Table 1, this results in only a 7% increase on the total workload of specialists, while reducing the total workload on ER by 20%. Also, because the visits to critical sub-path ER-H are reduced by 24%, the number of short-term hospitalizations (H) is 17% less under this scenario. Since H is the most expensive care-provider, this leads to a 14% cost reduction per stroke patient.

Scenario #2: Channeling 25% of the patients that go to ER during their first visit after discharge from hospital to F or G. Similar results to Scenario #1 are observed in both cases.

Scenario #3: Channeling 25% of the patients that go to H during their first visit after discharge from hospital to S, F or G. In contrast with scenarios #1 and #2, patients are diverted from short-term hospitalization rather than ER by increasing availability of other care-providers. Interestingly, no significant improvement is observed in the attributes we studied.

Scenario #4: Channeling 25% of the patients that go to ER after their first visit following discharge from hospital to a specialist. This scenario is studied in order to investigate whether the first visit show different characteristics than the following visits. As depicted in Table 1, under this scenario the workload of ER is decreased by 31%, the workload of H is decreased by 22% and average cost is also improved by 18%. Perhaps equally important are the 12% and 33% reduction in the number of visits to critical sub-paths H-H and ER-H, respectively.

Discussion

The scenario analyses summarized above indicates that avoiding ER visits of stroke patients is a means to improve health outcomes (i.e., reduce mortality rates), workloads (i.e., reduced load on ER) and average cost per patient. Based on our experience in the field, we believe that in many cases stroke patients find it necessary to go to ER since they do not have convenient access to other care-providers, in particular specialists, family physicians and general practitioners. Our results show that channeling 25% of those patients who visit ER to these care-providers leads to improvements in all the attributes we have studied. This amounts assuming that 25% of the patients end up in ER simply due to the unavailability of other care-providers, which we believe is a realistic assumption in the context of Québec. Of course, the proposed methodology allows for the use of more accurate data pertaining to the scenarios that need to be studied before a policy for system improvement can be designed.

It is important to note that ER does serve as the gate keeper for the hospital and a significant proportion of the patients are hospitalized for a short-term following a visit to ER. This is because some of the stroke patients become worse while waiting for a specialist or physician, before they feel that they need to visit an ER. Therefore, mitigating the ER visits also reduces the number of short-term hospitalizations, which constitute the most costly element of the care-delivery system. In addition, since ER-H is a critical sub-path, mitigating ER visits by increasing the availability of specialists and/or physicians would also reduce the mortality rate considerably.

References

1. Cote, M, Stein, WE. An Erlang-based stochastic model for patient flow. Omega. 2000;28:347-13.
2. Sinreich, D, Marmor, Y. Emergency department operations: the basis for developing a simulation tool. IIE Transactions. 2005;37;233-13.
3. Christodoulou, G, Taylor, GJ. Using continuous time hidden Markov process, with covariates, to model bed occupancy of people aged over 65 years. Health Care Management Science. 2001;4:21-5.
4. Davies, R, Johnson, D, Farrow, S. Planning patient care with a Markov model. Operations Research Q. 1975;26:599-9.
5. Gunes, ED, Chick, SE, Aksin, OZ. Breast cancer screening services: trade-offs in quality, capacity, outreach and centralization. Health Care Management Science. 2004;7:291-13.
6. Kao, EPC. Modeling the movement of coronary patients within a hospital by semi-Markov processes. Operations Research. 1974; June-August: 683-19.
7. Sugar, CA, James, GM, Lenert, LA, et al., Discrete state analysis for interpretation of data from clinical trials. Medical Care. 2004;42;2:183-14.
8. Thomas, WA. A model for predicting recovery process of coronary patients. Health Services Research.1968;3:185-29.
9. Weiss, EN, Cohen, MA, Hershey, JC. An iterative estimation and validation procedure for specification of semi-Markov models. Operations Research. 1982;30:1082-23.
10. Zon, AH, Kommer, GJ. Patient flows and optimal health-care resources allocation at the macro-level: a dynamic linear programming approach. Health Care Management Science. 1999;2;:87-10.
11. Akkerman, R, Knip, M. Reallocation of beds to reduce waiting time for cardiac surgery. Health Care Management Science. 2004;7:119-12.
12. Teng, J, Mayo, EN, Latimer, E, et al. Costs and caregiver consequences of early supported discharge for stroke patient. Stroke. 2003;34:528-9.

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