Re-designing policy and process in health care service delivery: a system dynamics case study

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1. Introduction

The health care industry in the United States represents one of the largest and fastest growing sectors of the economy, accounting for about 16.5% of US GDP in 2008. Rapid changes in the organization and financing of health care have put unprecedented pressure on health care delivery organizations to decrease costs and increase utilization, leading to a need to ensure that quality is not adversely affected (Hermann et al, 2000; Kertzman et al, 2003; Mitton and Donaldson, 2004). Health systems are plagued by problems with timely access to many services, as demand continues to rise in the face of increasingly tight budgets. Long wait times for emergency admissions, primary care appointments, and specialist referrals have prompted critical analysis and systematic re-design efforts over the past few years (Boelke et al, 2000; Murray and Burwick, 2003; Walley et al, 2006). Faced with such sub-optimal performance, healthcare managers are considering business process redesign, standardizing processes, and policy changes to solve service supply chain management issues (Young, 2004).

Effective health care delivery is dependent on the policy decisions made to respond to ever-changing demand patterns, regulations, and fiscal conditions. Policy decisions to manage health care systems are as relevant to ensuring quality care as the operation of individual clinical units (Forsberg, 2011). However, the ex-ante effects of most policy decisions or improvement initiatives are in some senses unpredictable, as health care delivery organizations are comprised of networks of discrete, yet interdependent, parts all influencing one another. This creates a vast number of possible outcomes from a single intervention, rendering health care a complex system (Bar-Yam, 2005). Dynamically complex systems result in situations where management decisions will provoke both intended and potentially unintended consequences (Wolstenholme, 2003). Developing a systems understanding of the causes of poor access (as measured by increasing wait times) is crucial to providing timely services and insuring effective patient access.

There is a clear need to assess the impact of proposed changes and improvement strategies on the cost effectiveness and operational performance of health care organizations (Smits, 2010; Young et al, 2004; Bower and Gilbody, 2005). The aim of this research is to support management decision making on the design of care processes by assessing the impact of proposed redesign initiatives. The research question in this paper is 'How does simulation improve the impact of business process redesign and policy on business performance?' To answer this question, we analyze the patient intake and disability assessment process at a Veterans Administration (VA) hospital, determine key performance indicators, and simulate the effects of changes in process design and policy. The hospital seeks to reduce exam lead times by re-designing capacity and resource adjustment processes through increasing the role of mid-level providers (physicians assistants and nurse practitioners) and moving away from employing specialists. They expect these process changes to have no adverse impact on quality or patient care and satisfaction measures.

The paper is organized as follows. First, we discuss the origins of the present study, provide background on the patient access problem and discuss the choice of system dynamics (SD) modeling approach. Then we present an overview of the existing intake and assessment process in the VA hospital (the Base Case Scenario) and define the alternative scenarios including policy and process redesign. We end with scenario testing, model results, and conclusions.

1.1 Origins of the present study

The work presented here is a collaboration between the New England Veterans Engineering Resource Center (VERC) and Worcester Polytechnic Institute, in a joint effort to explore the causes of the long lead times at the VA and to develop and test policies to counteract those delays. The New England VERC is part of a national effort by the VA to increase their capacity for health systems engineering and process improvement in an effort to both reduce health care costs and improve patient outcomes. The systems modeling of the disability assessment process was provided by WPI, while orientation to the problem area, introductions to stakeholders, and access to data used to parameterize the model were supplied by the New England VERC.

Initial qualitative research into C&P was completed in 2009 (Luk et al, 2010), and system dynamics was selected as appropriate methodology in late 2010. From October 2010, a one year study was proposed through a partnership with WPI professors and graduate students and VERC staff, funded by the New England VERC. A close working relationship was established with one VA hospital in the Northeast, which, for confidentiality, will be referred to simply as 'the hospital'. The model was calibrated with information held by hospital staff and from their electronic medical record system.

2. Background

Spending on intake and disability assessment by the VA (called Compensation and Pension) is around $317.6 million dollars per year. The backlog of people waiting for disability assessment by the VA has risen from 389,000 in 2009 to over 809,000 by 2011. Of this amount, over 60 percent have waited for over 125 days. The VA's FY2012 budget projects that the average days to complete a claim will rise to 230 days in FY2012 (An Examination of Poorly Performing U.S. Department of Veterans Affairs Regional Offices, 2011). For VA hospitals, Compensation & Pension is the clinical segment of a longer process through which Veterans petition for recognition of a service connected disability, which then grants them access to free health care for that disability and potential pension payments for lost employment. Simply put, it is the gateway to VA health services and benefits. All returning service members must navigate this process, as must all current VA patients seeking to change their recognized level of disability.

This paper focuses on the Compensation and Pension service (C&P) at one VA hospital. This hospital is a large, integrated care organization with a service area of around 470,000 people, treating 63,000 patients annually, with a staff of approximately 3,700 FTE, including primary care doctors, specialists, lab services, administrators and support staff. The organization provides primary and intensive care, specialty surgical services, emergency and urgent care, and both in- and out-patient mental health treatment.

C&P offers medical disability assessments for around 8,200 patients per year (FY 2010). Demand varies considerably, ranging from 1,138 to 1, 679 exams per month in 2010. C&P employs approximately 14.6 FTE people (in 2009), 1.4 generalists (MDs, physicians assistants and nurse practitioners), 0.8 psychiatrists, 5.4 specialists, and 7 support staff. The remaining staff needed are procured on an ad hoc basis from other departments inside the hospital, and from outside providers on fee-for-service contracts. These 'non-aligned' staff represent the bulk of the capacity used by C&P, acting as a buffer against fluctuations in demand.

Patients are referred to C&P solely by the Veterans Benefits Administration, which conducts the initial 'triage' process for assessing disability claims. After referral to the hospital C&P service, patients enter the intake process for exam scheduling and medical disability assessment. We analyze the linkages between the demand for services, assessment processes, and capacity adjustment decision frameworks. Conducting the disability assessments is the key business process, with about 80% of the staff conducting specialized disability exams (e.g., ischemic heart disease relating to Agent Orange exposure, or PTSD), and the remaining 20% required for administrative and clerical support. Again, these actual percentages fluctuate to as C&P managers attempt to match changes in demand.

The C&P management team is confronted with long waiting lists, long waiting times, limited personnel resources, and changing clinical and legal guidelines, as well as internal regulations and accreditation requirements. Long wait times for medical disability exams and a growing backlog of C&P claims have led to C&P becoming an important political issues, as veterans report dissatisfaction with lengthy processing times (Luk et al, 2010). More recently, the spectacle of Veterans committing suicide because of delayed treatment for PTSD has brought widespread criticism upon the VA (*New York Times*, 5. 6.2011). These actions and others prompted a series of Office of Inspector General investigations in 2008-9, in which they found inefficient, poorly coordinated services; scant resources; and low quality, as measured by the number of incomplete exams (Finn, 2010). These critiques have forced the VA and C&P management to initiate business process redesign efforts focused on efficiency and improving patient access.

Wait times are a key performance indicators for patient access to C&P services. The VA currently calculates wait times for one out of three phases in the intake and disability assessment process, as well as the total completion time for each assessment. The official guideline for the first phase, the scheduling phase (indicated as W1, in Figure 1), is three days. This is the time between receiving the request for assessment from the VBA and scheduling the exam(s) with the patient and provider(s). Over 60% of patients' assessments require multiple exams, with the average number of exams requested at 1.6 exams per patient. The time between the day the appointment is made and the day of exam (the assessment phase, or W2), and the time between completing the medical assessment and returning the claims report to the VBA (W3) are not officially tracked. The official guideline for the maximum total waiting time (W1+W2+W3, or from the time the initial claim is received by the hospital until the claim is returned to the VBA) is an average of 30 days. Average waiting times at the C&P study site, and nationally, often exceed the official guideline. The national average for medical disability exams was 34 days, and the average at the study site was 37.8 (FY2010).

These few, aggregate metrics do not provide enough detail to effectively manage or evaluate the C&P process. Focusing on only two aspects of the system (average wait time and reporting errors) allows other aspects of performance to remain out of control. Discussion with C&P managers revealed that some managers recognize this fact, and even though the distribution of wait times is not officially part of the VA's evaluation of C&P performance, some managers look for outliers by tracking the number of patients waiting for greater than 60, 90 and 120 days. However, these data are not linked to routine performance evaluation or process management, and are thus not easily collected or frequently examined. There are also no measures of cost used to evaluate C&P performance. Any calculation used to determine of the cost of a C&P program is based only on national average cost of provider time, and includes nothing specific to the C&P process (labs, space, clerical and administrative support, etc.). There is also no measure of diagnostic quality of the disability assessments, e.g., there is no peer review. Patients can appeal a VBA decision, which can initiate a re-evaluation by a new C&P clinician, but the appeal process is highly complex and often takes years. Peer review as a check on quality was deemed prohibitively expensive to the VA and cumbersome for the patient.

C&P management intends to change the design of its service provision process by transitioning from a specialty-driven practice to using more mid-level, generalists providers (physicians assistants, PAs, and nurse practitioners, NPs), as part of a general trend to reduce cost by keep clinicians 'working at the top of their licenses'. They believe PAs and NPs should be more productive than specialists, as they are able to conduct more types of medical exams and potentially conduct multiple examinations during the same appointment; moreover, the salaries of these staff are lower than those of specialists, which should lead to lower costs for C&P services. We were asked to determine the effects of these process changes on the effectiveness and efficiency of the C&P process. Analysis of C&P includes an assessment of the current disability assessment process, specification of performance indicators for effectiveness and efficiency, and modeling the Base Case and alternative scenarios for process design. We use the C&P case study to develop a simulation model of the intake and assessment process in VA hospitals and to define key performance indicators. We then use the model to simulate the effects of transitioning between providers to examine the trade-offs between resource cost, productivity, flexibility, quality, and patient access.

3. Use of system dynamics

Health care systems have been the subject of previous simulation studies. We briefly review this work and show the relevance of the system dynamics approach. A general discussion of the role of system dynamics in analyzing health care systems can be found in Taylor and Lane (1998).

As with all modeling approaches, the application of system dynamics produces gains as well as losses. Examples of the latter are the loss of the stochastic variation and resolution down to the individual patient, or condition level. However, the gain using system dynamics encourages both a systemic view of the interactions of patient flows and information, and a more strategic perspective of the management of the system. It is widely accepted by healthcare professionals that health care delivery cannot be understood by looking at factors in isolation (Lane, 1999). By encouraging the study of how different processes interact to produce effects, system dynamics offers a rigorous approach for bringing that interconnectedness insight into focus. Our decision to use the approach in this specific case had four components.

First, the objectives of our study – 1) to relate patterns of behavior to the system's structure, 2) to quantify the links between demand and patient wait times, 3) to assess potential policy levers for improving system performance – are mainly diagnostic in nature, necessitating the consideration of a broad range of interactions across processes. Second, the problem under analysis is 'dynamically complex', where process and policy changes often result in intended and unintended consequences, which cannot be easily foreseen without the help of a computer model (Kleijen, 2005). Third, the problem is 'long term', meaning that effect of process re-design decisions do not appear immediately but only after some months (Vennix, 1996).

Finally, the combination of modern software and group model building produces models which are both technically representative and persuasive to system participants. In this study, we worked closely with those who had knowledge of the system. By accessing their 'mental models' as well as formal sources (Forrester 1961), we were able to build a transparent model which was accepted as realistic in its formulation. The model became a 'visual learning environment'(Lane 1997), helping C&P management to understand why structure produced behavior (the Base Case) and how behavior varies under different management policies (the Policy Analysis). Making a complex and compelling mathematical model accessible to healthcare professionals can contribute powerfully to the policy making process and generate rigorous analyses for use in a broader policy context.

SD modeling has been used to address several healthcare related problems and has resulted in about 1500 publications since 1991 (Brailsford 2008). Dangerfield (1999) reviews system dynamics modeling in healthcare and concludes that the method can be used effectively in a qualitative way when influence (or causal) diagrams are the main analytic tool, and in quantitative ways when based on simulation models. Taylor and Dangerfield (2005) use quantitative system dynamics to analyze the reasons for failed management interventions in cardiac catheterization services. Lane and Husemann (2008) use qualitative SD modeling to elicit proposals for improvement of acute patient flows in the UK National Health Service. Wolstenholme et al (2006) use both qualitative and quantitative SD to analyze the effects of process re-design on mental health care performance.

We have not used discrete-event simulation (DES) or stochastic modeling (of variables like 'client inflow' or 'assessment time') because our primary objective is not to quantify numerical results but to understand and illustrate to the managers the deterministic behavior of their C&P system and understanding what causes poor system performance. For an in-depth discussion of the trade-offs and appropriate problems for using SD or DES see Tako and Robinson (2009) and Kleijnen (2005).

We use SD qualitatively to develop influence diagrams that specify relationships between management decision and their effects, and quantitatively through computer simulation. We develop the simulation model for C&P following the method described by Forrester (1994) and Sterman (2000):

1) Describe the system, including its parts and boundaries. We develop influence diagrams based on the internal reports, interviews with hospital staff, and the literature.
2) Convert these descriptions to level and rate equations, using Vensim DDS software.
3) Revise the model, until both model structure and outcomes fit the existing (base case) performance.
4) Design alternative policies and process structures, based on interviews with C&P managers, which are then simulated and compared to the base scenario.
5) Discuss the Base Case and alternative scenarios with C&P management.

Note that the sequence of steps 1-5 is iterated until the participants are satisfied and agree that the simulation model sufficiently represents reality. The final step 6 'implementing changes and policy structures' was not part of our analysis because the final decisions on policy and structural process changes would not be taken by C&P managers, but by hospital directors. We conclude step 5 with a policy recommendations report regarding our findings on the impacts of policy and process structure re-design on C&P performance and efficiency.

4. Model Development

First, we present a description of the existing process (the Base Case Scenario of specialized providers), followed by an influence diagram identifying all of the key management decision heuristics and information feedbacks. Combined, these inform the design of the simulation model, which is then presented with three scenarios for policy analysis.

4.1 The Base Case Scenario

We model the current situation as of June 2010 (when C&P was still in a relative equilibrium state, as represented by the Base Case Scenario). This model is based on internal management reports, interviews with managers, clinicians, and support staff in C&P. Seventeen semi-structured interviews were conducted with clinicians, clerks, operations and business managers, operating staff, and medical directors. Initial interviews with hospital staff were used to create a basic conceptual map outlining patient, personnel and information flows. In subsequent rounds of interviews, interviewees revised copies of the conceptual map, correcting or adding information so that it best represented their perception of the system. Revised maps were reviewed iteratively to develop the final conceptual map (later interviews used revised versions, though the basic structure remained similar). Then, they were asked to identify relative influences between system components and explain and quantify their own decision heuristics. The primary elements of this feedback model include the referral rate for C&P exams, exam scheduling, the backlog of exams waiting to be conducted, C&P staffing adjustments, and measures of quality and rework. Figure 1 shows a highly simplified version of the final map of the C&P process, consisting of the following phases:

- Patients are referred to C&P at an average rate of 153 patients per week (645 per month). After referral, patients enter the first waiting list (W1) to wait for a C&P clerk to contact them to schedule their appointment for a disability assessment. The average waiting time for an appointment is 1.3 days, with over 96% of all patients are scheduled within the 3 day guideline. The scheduling timeliness produced by each C&P support staff is monitored and addressed weekly by C&P management. This management feedback process ensures that adequate clerk time is devoted to scheduling patients. We found no linkage between scheduling and other wait times or backlogs; the changes in work pressure in other parts of the C&P process do not affect this performance indicator.

- After scheduling, patients enter the second waiting list (backlog W2), waiting for their appointment(s) for disability assessment. On average, 2,543 patients are waiting for their assessment, which consist of an average of 1.6 separate appointments, each with a different specialist provider. One patient may claim multiple disabling conditions, requiring multiple biologic systems to be examined (e.g., a patient may be suffering from joint pain, tunnel vision and depression). Appointments are conducted by a broad range of clinicians with varying specialization and productivity levels. A specialists can complete, on average, 0.63 of a patient's disability assessment in their one hour appointment. A physician's assistant can complete, on average, 0.87 of a patients disability assessment in their one hour appointment. 17% of patients are referred to C&P for three disparate conditions, 6% for four conditions, and only 1.3% for five or more. C&P management has near complete flexibility around assigning patients to specific providers (either to multiple specialists or a single generalist). However, there are a few conditions, such as PTSD exams, where a particular specialists is mandated by law. Approximately 5% of patients fail to report to their appointment, about 7 per week.

- After the appointment, patients enter a third backlog, waiting for their assessment report to be competed and sent to the VBA. This takes clinicians an average of 0.9 days. Some assessments are returned to the hospital as incomplete, unclear, or otherwise insufficient for use by the VBA. Reports with errors are discovered by the VBA after an average of 4.3 weeks, after which they are returned to the originating clinician. Correcting an assessment report requires approximately the same amount of time as the originating patient appointment, but very rarely (<0.1%) are patients required to return to facilitate this correction. The rework rate is reported monthly as a percentage of the entire C&P workload (not by individual clinician) and is between 1 and 2%. It should be noted that this quality measure does not measure the accuracy of the diagnoses, but simply familiarity with work process and VBA requirements.

In the equilibrium simulation, the outflow rate of complete assessments equals the inflow rate of requests for assessment. Therefore, on average, 146 patients leave the C&P process every week (accounting for the extra work done to correct errors and losses from patient no-shows). We estimate an average total assessment duration of 27.3 days, which compares reasonably to the process time of 26.9 days from calculations based on internal C&P reports.

The intake and assessment process in Figure 1 represents a stable situation, meaning that the available personnel resources in C&P have been allocated in such a way that the patient flows and waiting lists remain stable over long simulation periods. In reality, variations in referral rates, examination rates, and the availability of personnel resources lead to fluctuations in system performance (as measured by patient wait time and rework rate, as well as, unmeasured, in terms of cost and quality). The flows of patients through the C&P process strongly depends on the personnel resources assigned to each rate and the personnel resources needed per patient. These variables are determined directly by C&P management decision heuristics, which can be modeled as responses to available information on process performance. These responses create controlling feedback loops, where a rise in one performance measure (e.g., wait times) triggers a response (increasing personnel resources) that counters the initial change (wait times decline). The structure of these balancing feedbacks between referral rates, backlogs, and service capacity are crucial to the ability of the system to keep patient wait times within the desired range. Explicitly modeling each feedback loop creates a more robust understanding of the system and provides explanations for the observed system behavior.

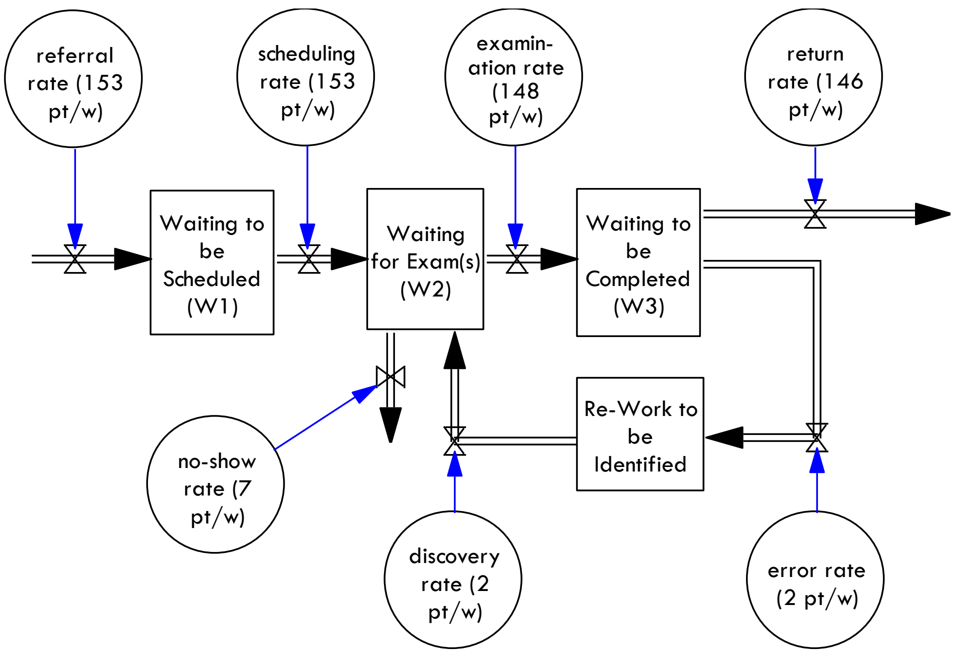

Figure 1. Overview of the intake and examination processes in C&P in June 2010. Rectangles represent stocks and circles represent rates or flows.

4.2 Influence diagram

Fundamentally, a system dynamics model is a causal theory of how behavior is generated by a system of both material flows and information feedbacks. Although no two C&P departments have the exact same problems, the nature of the main factors reducing access to services is universal. There are four main feedback processes interacting to affect patients' access to services. The principle interactions created by C&P management decisions and how these decisions influence the provision and availability of C&P services are shown in Figure 2. The C&P process contains the following feedback loops:

- Balancing Loop 1: Recruiting Personnel
  an increase in the number of patients waiting for exams increases the backlog and the expected patient wait time (C&P management uses the proxy measure 'average time until the next available appointment,' which is known continuously by clerks as they schedule patients). As this time increases beyond the target acceptable wait time, work pressure increases, leading C&P managers to hire more personnel. This results in more total personnel available to provide services, increasing the examination rate, which reduces the patient backlog and the proxy metric for expected wait time. In the Base Case Scenario, where C&P examiners are predominantly specialists from outside departments, C&P management increases personnel resources by 'borrowing' them from other services. Actual hiring of new staff is avoided because of the many delays inherent to the process: posting the position, filling the vacancy, accrediting the new clinician, specific training in disability assessments, takes, on average, 52 weeks.

- Balancing Loop 2: Adjusting Hours per Week
  similar to B1, as an increase in work pressure also leads C&P managers to increase the number of hours assigned per clinician per day (usually in the form of overtime). This causes an increase in the examination rate, which reduces the backlog, the average wait time, and the proxy metric for expected patient wait time. This feedback loop contains almost no delays, as changes to the number of hours each clinician is assigned to C&P can take effect the following day. This feedback is constrained by each clinician's willingness to work overtime. The few clinicians working directly for C&P (mainly PAs and NPs) have worked up to 20 additional hours per week. However, because most specialists are only temporarily assigned to C&P, they perceive C&P as secondary to their normal duties and are only willing to work up to two extra hours weekly for C&P patients. If work pressure declines, both generalists and specialists will reduce their C&P hours per day. In the Base Case Scenario, a predominance of specialists ensures that loop B1 dominates B2 in creating the dynamic tendencies of the system, as it is easier to increase service capacity by 'borrowing' more specialists than through increasing their C&P hours per day.

- Reinforcing Loop 1: Fatigue Buildup
  an increase in the number of hours worked per week will, with some delay, lead to an increase in fatigue (modeled as the effect of an exponential average of past month's total hours, see Sterman, 2000 for further explanation). This results in a decrease in the effectiveness of the personnel, reducing the exam completion rate. This reinforcing loop does not pose a problem in the Base Case Scenario, as the use of overtime is limited by the organizational constraints mentioned above. We assume that all staff (both specialists and generalists) experience the same effects of fatigue on productivity for the same accumulated overtime.

- Reinforcing Loop 2 (a and b): Work Quality
  addresses changes in work quality. R2a depicts how increasing fatigue creates an increase in the percentage of errors made, increasing the number of exams returned by the VBA for correction. This reinforcing loop causes the unintended consequence of increasing the backlog of exams (as this rework is added to the queue), further increasing work pressure and the need for more hours assigned per clinician per day to C&P. Loop R2b indicates that hiring also adversely affects average quality, as clinicians new to C&P will produce more errors than those with accumulated experience. We found that, on average, specialists take more time to gain experience than generalists, as specialists see fewer C&P patients per week (generalists can see up to 10 patients per day, while most specialists see an average of 4.3 patients per week in the Base Case Scenario).

Based on our discussions with C&P process stakeholders, we employed three main abstractions from the actual C&P process. First, we determined that the backlogs W1 and W3 do not contribute to the dynamic behavior of the system, as no relation was found between them and other system components or performance measures; thus, they were subsumed into the backlog W2. This reduction in model accuracy allows for a more clear interpretations of the causal factors producing the behavior observed in simulation. The second abstraction made was to start each model with the appropriate number of clinicians, regardless of type, for the Base Case Scenario initial referral rate. This prevents model initialization errors from confusing actual dynamic behaviors. Finally, in conjunction with C&P management, we made the decision that analysis of policy and process changes should only compare scenarios where personnel resources consist of all specialists or all generalists. In reality C&P is currently, and must continue to be, composed of a mix of generalists and specialists, and in no case could staffing with only one or the other be a feasible policy. However, C&P management felt that such abstracted scenarios were more useful for comparison and decision-making purposes, allowing for more clear answers to their questions on process re-design.

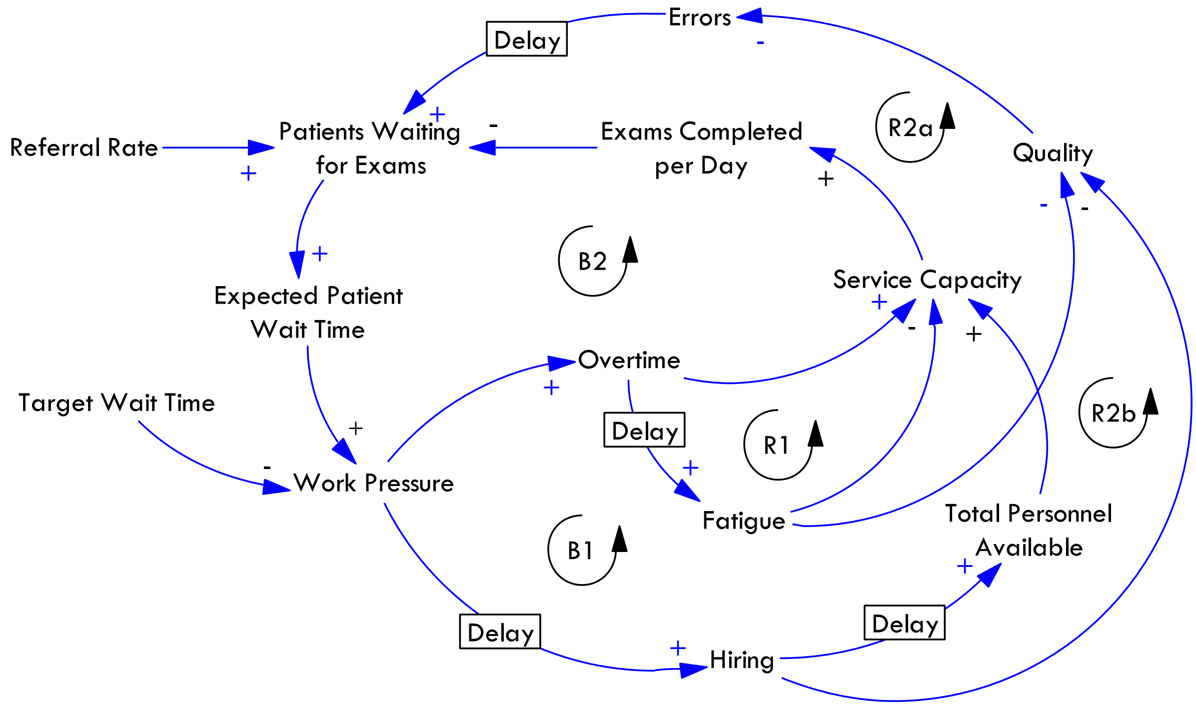

Figure 2. Influence Diagram of the main effects determining waiting time in C&P. The polarities of the causal links are: '+' = variables move in the same direction, '-' = variables move in the opposite direction.

5. Base Case Simulation

We use the overview of the current process (Figure 1) and the influence diagram of C&P management decision processes (Figure 2) to clarify thinking and to discuss process redesign, policy decisions, performance indicators, and the items to include in the simulation model. The model has nine stocks and 38 other variables, (plus 26 stocks and variables to calculate performance measures). Although the software has the ability to display the model graphically, we show a simplified map which effectively presents all systemic interactions (Figure 3). The model was constructed using Vensim® modeling software.

5.1 Behaviors in the steady-state

Calibration of the patient referral rate to C&P was derived from historical data made available by the hospital. These data are simulated as stochastic variation around a mean of 153 patients per week, or the equivalent of 1,025 exams per month. To establish the steady-state dynamics created by this variation around the mean patient referral rate, the model was run 1,000 times for the equivalent of three years each. Summary statistics from these runs are shown in Table 1. Unless otherwise stated, these performance measures have been calculated from the steady-state region and are averages subsuming the variation caused by the referral rate.

The measures calculated include a weekly average across all patients for the total delay time (from the initial request arriving at the hospital to the assessment report being sent to the VBA); this also includes potential rework delays. The minimum and maximum of this total waiting time are also calculated. Other measures track weekly average figures for error production, total service capacity, and clinician time utilization rates.

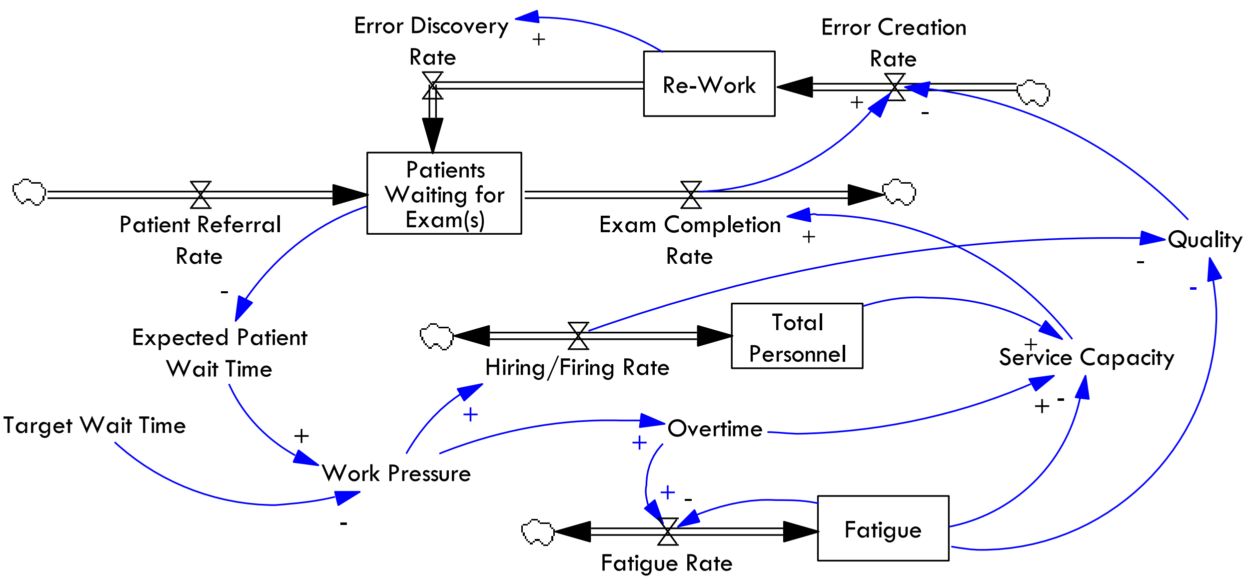

Figure 3. Stock and flow diagram of the C&P system dynamics model. Only the high level map is shown; the full model consists of 143 equations, 9 levels, and 11 rates.

The output from the Base Case Scenario was used to analyze the functioning of the C&P system in finer detail. Both historically and in the Base Case steady-state, average total patient wait time remains below the 30-day guideline more than 91% of the time. This slight variation in average total wait time is caused by the delays and constraints in adjusting service capacity to match changes in demand for services. The management structure in the Base Case is flexible enough (including both hiring or 'borrowing' and clinician's overtime preferences) to respond adequately when variation in demand for services remains within the bounds of what is considered steady-state. Adequate flexibility, in this instance, is defined as responding both quickly and sufficiently to ensure no sustained buildup in the patient backlog. The underlying causal relationships linking these two factors are analyzed below.

In the Base Case Scenario, the largest contributor to patient wait time arises from delays in the balancing loop B1, which represent management decisions seeking to adjust number of providers available to match demand for C&P services. C&P managers change desired workforce proportionally to match the changes in the expected wait time determined by the average time until the next available appointment. In the Base Case, managers are constantly negotiating with specialty service chiefs to adjust personnel allocations to C&P. The personnel re-allocation process takes an average of four months, consisting of negotiations between service chiefs, internal negotiations with clinicians, and updating clinic profiles in the IT system. During this time, service demand has undoubtedly changed, prompting another round of negotiations. Thus, C&P personnel resources are always four months behind what C&P managers believe they should be. However, this delay leads to limited adverse consequences during normal fluctuations in demand for services. As shown in both simulation and site data, a four month personnel adjustment delay is not enough to allow a buildup of patients waiting for appointments. Under normal conditions, neither the speed nor the volume of the responses generated by this loop are too limited for managers to be able to keep C&P performance close enough to desired.

Table 1. Performance measures for the Base Case Scenario

	Average total patient backlog [patients]	*Average service capacity [FTEE]*	*Total waiting time (min. avg. max.) [Days]*	*Average C&P report insufficiency [%]*	*Average daily C&P clinician utilization [%]*
Base Case Scenario (Avg. referral rate 153 patients/week)	2,451	33.2	24.6, 27.3, 30.1	1.34%	97.1%

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C&P managers can also adjust service capacity by directly changing hours per clinician, represented by balancing loop B2. However, this loop has little effect on overall service capacity in the Base Case. No large adjustments to C&P hours per week are possible, as 'borrowed' specialists have no incentives to work overtime, and a reduction in clinic utilization (working less than an 8 hour day) would cause their specialty service to re-requisition them to their primary service. While balancing loop B2 is not constrained at all in speed, it is severely constrained in terms of volume of response available.

The organizational structure in which C&P is embedded leads to a dependence on loop B1, the official re-allocation of resources between departments. This lack of an immediate lever to change service capacity, coupled with the delay in resource re-allocation, prevents C&P managers from reacting optimally to changes in demand for services. These two factors combined lead to the observed 9% overage in patient wait times.

5.2 Excess demand for services

The Base Case Scenario also includes a period of excess demand for C&P services. This excessive demand overloads the C&P system, creating a massive patient backlog and increasing average total wait times to near 50 days. Figure 4 compares historical data, with a 160% increase in demand for services during July and August 2010, to the Base Case simulation output (one sample run shown). The model replicates historical behavior, where normal variation in the patient referral rate produces a tolerable variation in total patient waiting time, until a period of excess demand creates a subsequent increase in average patient wait time. The underlying reasons for this behavior are analyzed below.

When demand for services is inside this 'steady-state' range, system's management structures contain tolerable delays and constraints, producing limited variation in patient wait time. However, historical data indicate that the system is not robust against a rapid increase in demand for services outside this range. In this situation, the four month delay in personnel resource re-allocation in Loop B1 is too long to maintain desired system performance. The delays in C&P system response time, coupled with the constraint on the more immediate service capacity adjustment loop, balancing loop B2, allow a considerable backlog of patients to develop before adequate service capacity is allocated to C&P. The backlog immediately following the period of excess demand in July and August 2010 reached over 5,000 patients, an increase of 250% over the average 'steady-state' backlog.

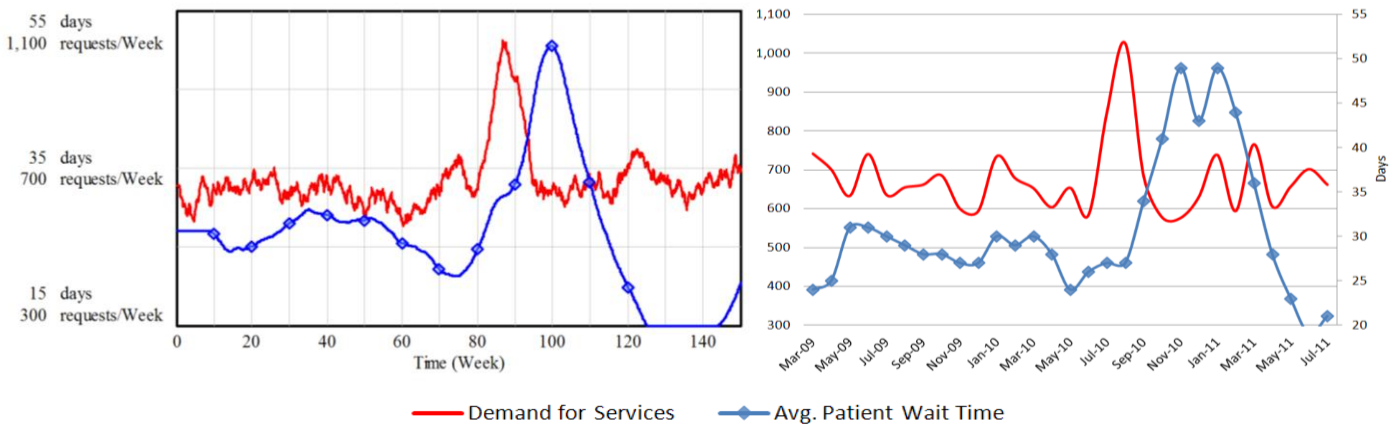

Figure 4. C&P referral rate and average patient wait time. Right: Historical data from C&P service from March 2009 through July 2011. Left: Output from a representative Base Case simulation run

Moreover, increasing personnel levels creates the additional challenge of temporarily lowering the average productivity (loop R1). Interviews with C&P medical directors and clinicians suggest that clinicians new to C&P exams are only 50% as productive as experienced clinicians. While not a driver of system behavior in the base case, as the proportion of new to experienced providers is relatively static, management responses to this sudden demand increase create productivity reductions which exacerbate the patient access problems. Bringing in new, less productive clinicians, reduces average productivity just when managers need the most from their staff.

Increasing C&P personnel levels also adversely affects service quality (loop R2b). Just as new clinicians take more time per exam, they also make more mistakes per exam than more experienced clinicians (while not diagnostically less proficient, they have less understanding of reporting terminology and the nuances of the C&P IT system). C&P managers found that new clinicians were twice as likely to make a mistake than experienced clinicians. It takes the VBA, on average, one month to discover these reporting errors, resulting in a secondary surge in total demand as this re-work is returned for completion.

These two reinforcing loops combined simultaneously create an increase in rework, further increasing the backlog of pending exams when it is already above normal, and a decrease in the ability of C&P to (re-)do those exams. The long-lasting effects of these ‘side effects’ to management’s response to the demand surge can be seen in Figure 5, where rework is shown to account for up to 25% of the total C&P workload after the simulated surge in demand.

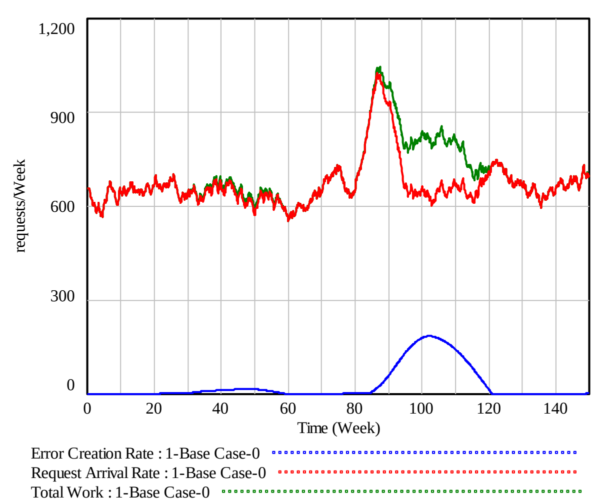

Figure 5. Base Case Scenario simulation output for patient referral and error rates contributing to patient backlog.

Delays in balancing loop B1 also lead C&P managers to request more capacity than is actually needed to return patient wait time to within the desired range. Delays between initiating personnel adjustments and the observable effects of those adjustments are not captured by performance measures in the system, or in the decision heuristics of C&P managers. This information gap leads to an overshoot of the optimal personnel adjustments, producing a period of excess capacity. Loop R1 reinforces this effect, as clinicians who were previously new to C&P and, thus, working at below-average productivity, improve their performance over time, further increasing effective capacity only after the demand surge has passed. These management structures create an overshoot which can be seen in both the below-average patient wait time at the end of both the historical data and in the simulation (in Figure 4 from June to July 2011 in site data, and in weeks 120-150 in simulation) and in the reduced clinic utilization rates of C&P clinicians over the same period.

We have derived a system structure from iterative interviews and site data that reproduces observed behavior. In analysis of the Base Case simulation, we have clearly defined the problem facing C&P. Simulations reveal a system robust against what is perceived to be a 'normal' level of demand volatility, but not against 'surges' in demand, or increased levels of demand volatility. C&P management decision structures reliant on borrowing specialist clinicians are not flexible enough (in terms of response speed) to prevent a buildup of patients waiting for appointments when demand increases suddenly. If demand is subject to recurrent sudden increases, then further patient access problems are inevitable.

C&P managers believe changing to a different type of provider, one that is more flexible (can conduct more types of exams) and has higher average productivity (can conduct multiple exams simultaneously) will allow the system to respond quickly and adequately when faced with future surges in demand. Simulation allows us to confidently test this policy change, along with others, before implementation. Simulation also allows us to challenge managers' assumptions on the causes of the observed behavior in the system, and assess the robustness of new policies under different demand conditions.

6. Policy Analysis: exploring scenarios using model simulations

The initial motivation for this research was to inform process re-design efforts by one VA hospital facing a 'crisis' of patient access to services. Model simulations explore what changes to current system policies or processes could render the system more robust against fluctuation in demand for services, and to prevent future sudden increases in demand from re-creating the access problem seen in 2010. The developed model was used to conduct a range of simulation experiments for comparison with the Base Case Scenario. The principle scenarios involve changes in provider type in C&P, changes to the structure of the C&P service system, inclusion of extra service capacity to act as a buffer against referral variability, and combined scenarios. Other policy runs explore the effects of increased demand volatility.

Policies were judged against current national guidelines for timeliness (total average patient wait time <30 days) and quality (<2% disability assessment return rate). However, discussion with our collaborators indicated that other performance indicators would be useful for evaluating C&P performance. Hospital administrators and C&P managers sought to compare clinic (e.g., provider) utilization, total cost, productivity, and cost per patient across the various process re-design alternatives.

The resulting total of seven key performance indicators are listed in Table 1, left column (equations for performance measure calculation are shown in Appendix 1). The first two indicators are the national performance indicators currently tracked by the hospital. The next indicator is total cost per year, which is based on number of providers and hours worked per week (this measure includes the extra costs of overtime and under-time, but excludes fixed costs, tests, labs, administrative and support staff, etc). The next three indicators are measures of productivity: Clinic utilization is the ratio of actual time spent in C&P to a standard 40 hour workweek; average productivity is measured as exams/hour (which is affected by ratio of new to experienced providers and fatigue from excess periods of overtime), and cost per patient. Finally, we present our own measure of timeliness: the average absolute difference between the target wait time and the actual wait time (i.e., the accumulation of all wait time error, averaged over the duration of the simulation). This is a more descriptive measure of the C&P system's response to fluctuations in demand for services than average total wait time. Average total wait time can be a misleading performance indicator, as a lower average wait time is not necessarily a sign of improved performance. An average wait time below the target wait time indicates the system is providing faster than desired access to services, and is thus consuming more than the necessary level of resources. We do not include indicators of patient satisfaction because we assume these are constant in our model, and thus do not affect model behavior. General patient satisfaction with the disability assessment process is outside the scope of our research efforts, but future models may include measures of patient satisfaction.

6.1 Provider type & structure scenarios

System behavior was simulated for various provider types in C&P. The two types chosen by our collaborators to be of interest were staffing with all specialists and all generalist (specifically, physician's assistants). These scenarios test the implicit hypothesis underpinning the current process re-design, that staffing with PAs will both reduce cost and improve timeliness, as generalists have lower average salaries and can complete more of the average patient's request than a specialist.

We also simulate changing the organization structure of C&P: instead of 'borrowing' providers from a distributed network of C&P-trained clinicians throughout diverse departments and specialties, staffing is centralized, where all C&P clinicians are hired (not borrowed) directly into a C&P department, and report directly to a C&P director. This increases their willingness to work overtime when demand increases and the ability of C&P managers to schedule under-time when demand decreases. Modeling changes to C&P system's structure also includes effects on managers' decision heuristics, providers' learning rates as related to gaining experience, and employee turn-over rates. Modifying system structure tests the conclusion of the Base Case simulation analysis, that in-house 'borrowing' of providers is *not* flexible enough to accommodate the observed history of demand fluctuation.

The resulting performance measures (see Table 2) and analysis of the various outputs of the runs, reveal the trade-offs between these two staffing policies and these two system structures. Mean total wait time appears to support the initial process re-design hypothesis, that 'borrowing' clinicians creates a more flexible system resulting in better performance indicators than hiring permanent clinicians. However, the variation in total wait time is reduced when staffing with PAs; lowered to 28.7% of the range of the Base Case. The maximum average patient wait time in the centralized-staffing scenario is only 37 days, compared to over 50 days in the distributed-staffing scenario. For comparative purposes, the clearest measure is absolute wait time error, which is the total accumulated difference between the actual wait time and the target wait time. The centralized-staffing scenarios generates only 28% of the wait time error accumulated during the Base Case and other distributed-staffing simulations.

This counter-intuitive result reveals that hiring permanent clinicians renders the system more able to adjust to highly variable demand for services than borrowing temporary clinicians. The trade-off between a long time to hire (~52 weeks) against a short time to borrow (~16 weeks) is off-set by the added flexibility in the case of centralized clinicians of near-instantaneous adjustments in hours assigned per week. This improved performance is not the result of C&P managers demanding excessive work hours from their clinicians: average clinic utilization is just 2% above the Base Case scenario. Improved system performance is generated by a greater ability to use of both overtime and under-time, as C&P managers are better able to counter changes in referral rates with changes in hours per clinician per week.

Table 2. Performance measures for four process re-design scenarios

Performance Indicator	*unit*	*Scenario*			
		Base Case = Distributed Specialists (100%)	*Distributed Generalists*	*Centralized Specialists*	*Centralized Generalists*
Total waiting time (min. avg. max.)	*[days]*	13.2, 26.3, 50.5	13.2, 26.3, 50.5 (100%)	23.9, 27.2, 37.4 (103.4%)	23.9, 27.2, 37.4 (103.4%)
Average report insufficiency	*[%]*	3.15%	3.15% (100%)	0.54% (17.1%)	0.54% (17.1%)
Average total cost	*[dollars / year]*	$5,707,000	$2,066,000 (36.2%)	$4,587,000 (80.1%)	$1,661,000 (29.1%)
Average clinician utilization	*[%]*	99.06%	99.06% (100%)	101.7% (102.1%)	101.7% (102.1%)
Average clinician productivity	*[exams / hour]*	0.475	0.654 (137.7%)	0.593 (124.8%)	0.816 (171.8%)
Average cost per patient	*[$ / patient]*	$3,841	$1,391 (36.2%)	$2,795 (72.8%)	$1,012 (26.3%)
Avg. absolute waiting time error	*[days]*	6.07	6.07 (100%)	1.74 (28.7%)	1.74 (28.7%)

Changing type of provider does not affect wait time, exam quality, or clinic utilization rates. It is the C&P system's ability to respond to demand that determines the wait time error. The more flexible the system, meaning the fewer constraints in speed and size of service capacity adjustment, the better that system will be able to maintain a desired wait time when faced with fluctuating demand. Changing individual provider productivity has no long-term effect on maintaining patient access to C&P services (increasing productivity will decrease wait times when demand is above capacity, but it will not improve performance generally).

A centralized organizational structure also generates the added gains of greater productivity due to lower clinician turnover (the average clinician will work in C&P for years instead of months). This causes an increase in exam quality (as measured by the exam return rate) over the Base Case. Exam quality in the model is determined by the effects of fatigue and experience, and is assumed not to be affected by inherent differences in skill sets between specialists and generalists. Long periods of overtime could lead to fatigue and reduce quality (included in the model in feedback loop R2a), and while clinic utilization does increase in slightly under centralized staffing, it is not enough to affect performance. The effects of different demand pattern on clinic utilization rates are examined in subsequent simulations.

Changing provider type only affects costs and average productivity levels. In both distributed-staffing scenarios and centralized scenarios, switching to generalist reduces the cost of providing C&P services by 63.8%. Most of these gains are generate by differences in base salary, as generalists' salaries are assumed to be, on average, 50% of those of specialists. Clinician productivity, as measured by the number of C&P requests completed per hour, is also higher for generalists than specialists, reducing the total FTE required to meet demand, further reducing costs. These factors combine to affect average cost per patient, which is significantly lower with generalists than with specialists. The lowest cost per patient is found in the combined scenario, with centralized staffing of generalists. This scenario combines the inherent cost savings and productivity gains with the more subtle benefits of improved average experience-level from decreased employee turnover.

Each re-design scenario addresses some aspect of system performance. Changing provider type affects cost and productivity, while changing system structure affects patient access and exam quality. Thus, the hospital's initial process re-design plan would have improved system performance, but not in the expected direction: the model suggests that costs would have decreased, but the planned changes would not have led to improved patient access. The largest improvement comes from changing both the provider type and the system structure in which those providers work. This combined scenario increases patient access and reduces cost simultaneously (see Figure 5).

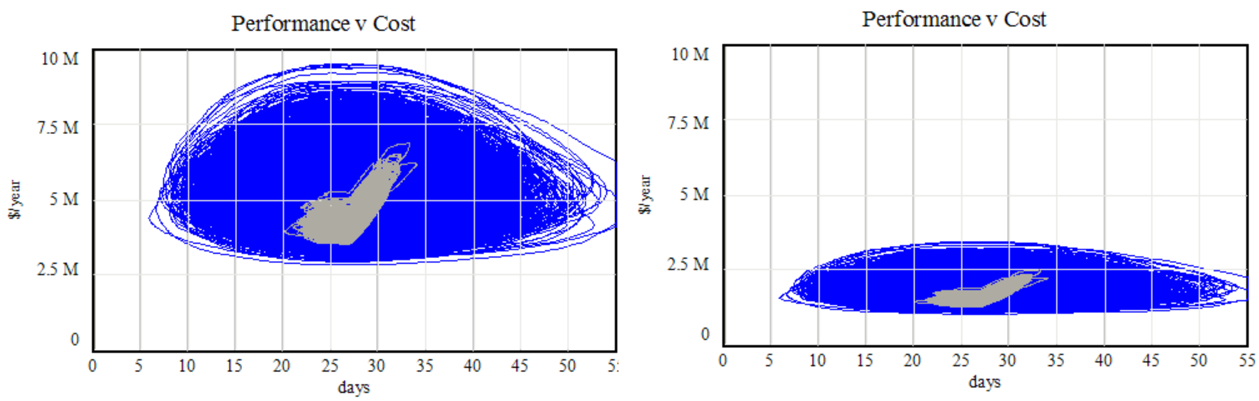

Figure 5. Comparison of average patient wait time to total costs under four scenarios, 1000 runs each. At left: Specialists, right: Generalists (distributed staffing in blue and centralized staffing in grey).

6.2 Introduction of 'buffer' capacity

These scenarios test the hypothesis that including 'buffer' personnel renders the system more able to absorb shocks, and thus reduces average patient wait time when faced with periods of excessive demand for services. We ran four scenarios, one for each provider type and system structure, where the initial and desired staffing level was increased by 10% over the previous scenarios.

Under both types of clinician capacity, adding additional capacity does cause general downward pressure on wait time. For a C&P staffed from a distributed network of providers, the addition of buffer capacity reduces the average wait time by 8%; including a buffer capacity for the centralized-staffing scenarios reduces average wait time by only 4%. The additional staff constantly reduce the backlog faster than necessary, driving down average wait time below the desired average wait time. This imbalance is most evident in measures of absolute wait time error, which is higher in all four scenarios with 'buffer' capacity than in the Base Case, even though the average wait time is lower. The increase in total average wait time error ranges from 3% from the centralized generalists scenario and 9% from the Base Case scenario. In all scenarios, introducing buffer capacity also increases the cost per patient by between 2% and 4%.

While this policy does generate a small reduction in average wait time for a small increase in cost, it yields almost no benefit when comparing the size of the variation in patient wait times. The range of the patient wait time generated under each provider type is almost identical to the range without the 'buffer' capacity. Simply put, an additional 10% service capacity is not enough to cushion against the near doubling of the referral rate faced by the C&P department in these scenarios. In the Base Case (when a staff of distributed specialists is faced with a sudden increase in referrals), average patient wait time ranges from 13 to 50 days over the course of the simulation, for a total range of 37 days. In the simulation of the same scenario with the addition of 10% 'buffer' capacity, that range is still 37 days, albeit shifted by three days, for a minimum of 10 days and a maximum of 47 days. With this provider type and system structure, the 'buffer' capacity would need to be 57% the size of the total capacity to achieve the same backlog mitigation seen in the centralized scenario, which, if implemented would pose a significant burden to the hospital budget. This analysis suggests that hiring extra personnel is not an effective buffer against sudden changes in referral rate, and addressing variation in patient wait time through over-staffing is unrealistic and inefficient.

6.3 Referral pattern scenarios

The response of the model to a permanent change in the dynamics of the referral rate of C&P patients is examined. The aim is to explore how the system would behave under rising demand for services and to investigate system behaviors obscured by the randomness introduced in previous scenario tests. We examine two scenarios, one where demand increases from a constant level to linear growth, and a second scenario, with a sudden, permanent increase in demand. The first simulations were prompted by possibility that demand for services will indeed rise over the coming years. C&P managers were eager to test the system's robustness against this plausible scenario. The second set of simulations is a more abstract test of system performance. Testing the model against only one change in demand, as opposed to the continuously changing demand in all other scenarios, is the clearest way to reveal inherent patterns of behavior in the system's response to changes in demand.

Under constantly increasing demand, the system is able to maintain it desired level of service performance with minimal error. Delays built in to the distributed structure lead to continued oscillations in average patient wait time. The more flexible centralized structure also produces oscillations, but they have smaller amplitude and dampen quickly (note: the type of provider does not affect the behavior of patient wait time, but does affect cost per patient – see Figure 6, below).

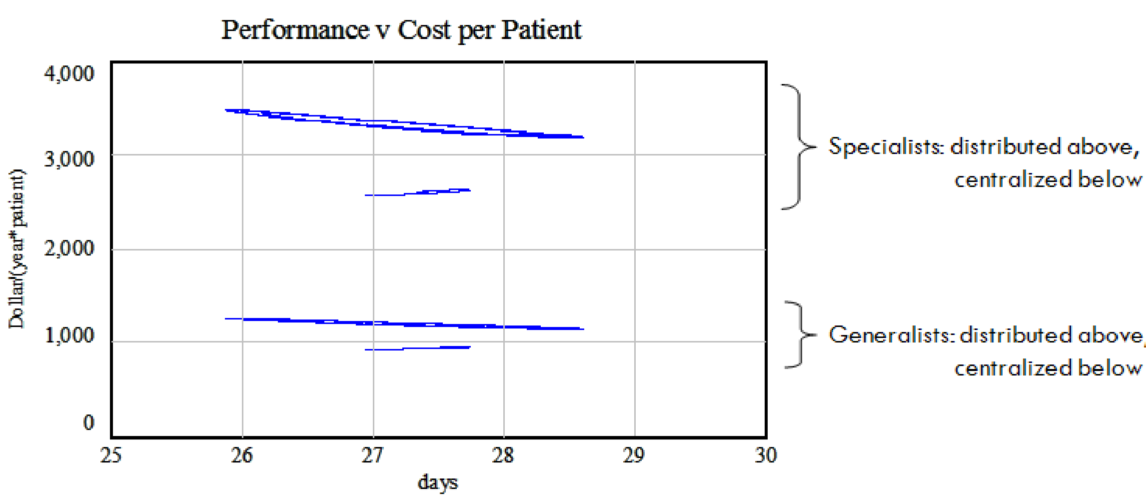

Figure 6. Comparison of cost per average patient to average patient wait time under four scenarios with linear increasing demand.

If the system is presented with a sudden, permanent increase in demand, the effects of different organizational structures become even more clear. Under the current, distributed structure, one change in demand leads to continued oscillations in patient wait time. While it is impossible to see this in the historical data, as demand and other process parameters are always subject to small fluctuations, this result further supports the dynamics hypothesis that centralized staffing is more able to absorb changes in demand for services than a distributed staffing structure.

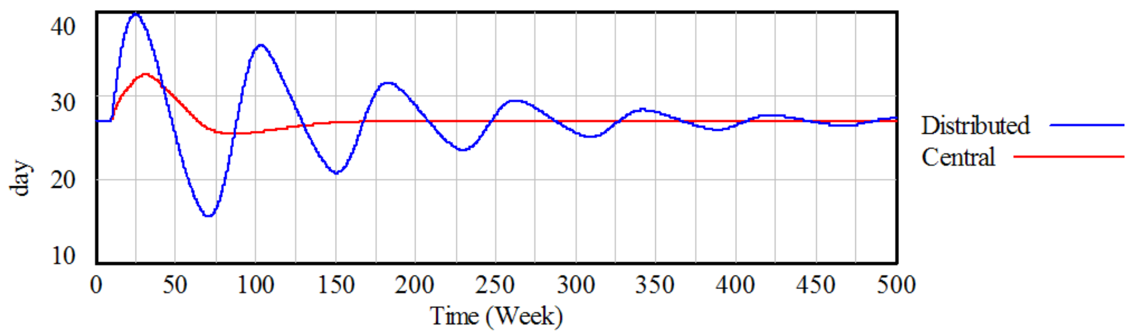

Figure 7. Comparison of behavior of average patient wait time under four scenarios with a 25% instantaneous increase in demand for services at Week 10. Centralized staffing structure responds with less oscillation, regardless of provider type.

7. Comments and conclusions

This work yields specific, practical lessons for C&P departments across the country, as well as more general conclusions for the management of the service delivery systems. Additionally, elaborations and uses of the model beyond health care are possible.

The principle message of this study is that, when facing volatile demand for services, increasing system flexibility yields more improvement than increasing or otherwise changing personnel resources. Problems with timely patient access are generally better alleviated by creating a system structure that allows for more rapid response to demand than simply increasing the total service capacity available. Increasing total personnel without increasing flexibility yields expensive, yet limited, improvement. The ability to make swift and adequate adjustments to service capacity make it possible to achieve better performance while simultaneously reducing costs.

The ability of a C&P department to respond to demand variability determines its performance over time. These simulated scenarios indicate that without changes to C&P management's ability to adjust assigned hours per week, there is limited service capacity flexibility, which inevitably result in periods of lengthy delays for patients. Changing provider type has no effect on patient access, but has a significant effect on average cost and productivity. These simulations also demonstrate that increasing personnel levels alone cannot compensate for variability in the demand for services. For a C&P department to improve performance on all performance measures, managers should both change provider type to reduce cost, and centralize those providers to improve system responsiveness.

This study also illustrates the value of simulation modeling in health care management and process re-design. The qualitative conceptual map provides a useful structure to base the stakeholder interviews, and provided, often for the first time, C&P managers with a holistic view of the system where they could finally clearly see the interactions between their own decisions, process steps, and performance metrics. Simulation modeling provides an investigative tool that permits comparison of the relative benefits and probable costs of various change options. It is also a learning laboratory which permits risk free experimentation and encourages creative thinking and imaginative solutions. This case study demonstrates the potential for health care simulation to contribute to process re-design initiatives and ultimately its potential value in reducing health care costs, increasing performance, and improving patients' access to care.

Appendix 1: Calculations for Performance Measures

Total waiting time (min. avg. max.) = Maximum, Average, and Minimum of Delivery Delay

Delivery Delay = Service Backlog/Request Completion Rate

~ Week

~ The average time to complete customer requests is determined by Little's Law as the ratio of the backlog to completion rate.

where:

Average Delivery Delay = Maximum value of (INTEG(Delivery Delay, 0)/Total Time)

~ Week

Average report insufficiency = Maximum value of ("Avg. Insufficiency Rate")

= (
INTEG(Error Creation Rate/Request Completion Rate)
)/Total Time

~ Dimensionless

Average total cost = Maximum value of ("Avg. Cost - Salary" + "Avg. Cost - SalaryOT")

= (
INTEG ("Yearly Cost of C&P - Salary" = (Total Employees*Cost per Employee), 0)
+
INTEG ("Yearly Cost of C&P - Salary OT"= ((IF THEN ELSE(Workweek>Standard Workweek, (Workweek/Standard Workweek)-1, 0))*Total Employees*Cost per Employee)*(OT Cost Ratio), 0)
)/Total Time

~ Dollar/year

where:

OT Cost Ratio = 1.5

~ Dimensionless

~ Salaried employees make time and a half if they work overtime.

Cost per Employee = IF THEN ELSE("Clinician Switch, 1=PA"=1, 75000, 150000)

~ Dollar/year/Employees

~ Specialists make $150,000 per year and PAs make $75,000 per year.

Average clinician utilization = Maximum value of ("Avg. Clinic Utilization Rate")

= (INTEG(Workweek/Standard Workweek, 0)
)/Total Time

~ Dimensionless

Average clinician productivity = Maximum value of ("Avg. Productivity Rate")

= (INTEG ((Service Capacity/Total Employees)*(Standard PDY), 0)
)/Total Time

~ requests/Employees/hours

~ Average productivity for Total personnel.

Average cost per patient = Maximum value of ("Avg. Cost per Patient - Salary")
= INTEG(ZIDZ(("Yearly Cost of C&P - Salary OT"+"Yearly Cost of C&P - Salary"), Service Backlog) * "Avg. Requests per Patient", 0)
/ Total Time)
~ Dollar/(year*patient)

where:
"Avg. Requests per Patient" = 1.6
~ requests/patient

Avg. absolute waiting time error = Maximum value of ("Avg. Absolute Delivery Delay Error")
= (INTEG((ABS(Delivery Delay-Target Delivery Delay))*"Days/week" , 0)
/Total time)
~ day

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