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SIMULATING HEALTH CARE SYSTEMS: A TUTORIAL

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ABSTRACT

This paper is an introduction to discrete event simulation for modeling the operations of healthcare systems. It begins with a brief discussion on the use of simulation to model various areas of healthcare systems. These models were developed to support decision making, to gain a better understanding of the operations of these systems, or to determine how these systems can be improved. The tutorial provides an overview of the simulation modeling process, with a focus on model conceptualization to visualize healthcare systems. An example of an endoscopy clinic is used to convey model conceptualization and the power and flexibility of this modeling methodology.

1 INTRODUCTION

One of the earliest applications of simulation for modeling healthcare systems was a study by Levine (1969). The model enabled the assessment of the benefits of multiple configuration, under multiple operating policies, of an automated hospital emergency command system to adequately respond to individual patients emergency situations. Levine's effort was programmed for an IBM 360-75. A lot has happened since then! The last five decades have seen hundreds of papers appearing in the literature reporting the use of simulation to support decision making for *public policy*, *patient care delivery planning*, *operating policies*, *capital investment*, and *epidemiologic processes* (Standridge 1999). Many of these articles have been presented at conferences such as the WinterSim, INFORMS Meeting, IIE/IERC, and IIE's Healthcare Systems Process Improvement Conference, among others. These forums have enabled interactions among healthcare systems managers, simulation software vendors, simulation practitioners, and researchers, leading to a better multidirectional understanding of needs and capabilities (England and Roberts 1978; Fone et al. 2003; Brailsford et al. 2009).

This tutorial is focused on using discrete-event simulation to model healthcare delivery systems, with the purpose of better understanding the stochastic behavior of these systems and identifying ways to improve the operations of these systems. It does not address the use of simulation for disease spread, or similar epidemiologic processes.

Section 2 presents a brief historic background on the use of simulation for modeling health care systems. Section 3 describes the simulation modeling process. Section 4 discusses an example to show the flexibility of simulation to model and analyze healthcare systems. Emphasis is on model conceptualization and establishing inputs to provide a means to go from a healthcare subsystem to a simulation model of it. Section 5 discusses some challenges in modeling these systems. Section 6 gives a

summary and mentions newer ways to use simulation for the modeling and analysis of healthcare systems.

2 BACKGROUND

In an early review of the literature on healthcare modeling, Fries (1976) identified fifteen categories of areas of application of modelling in general (mathematical / simulation), which included demand forecasting, ambulatory services requirements, health planning, and so forth. A comprehensive review and analysis of the literature by Brailsford et al. (2009) revealed an exponential trend on the number of articles on simulation and modeling in healthcare. In fact, 82% of the articles published between 1957 and 2007 appeared in the literature after 1990. Approximately 28% of the reviewed articles used simulation as either the primary or the secondary method (Figure 1, top series), and of these, about 55% used discrete-event simulation. A quick review of the proceedings of the Winter Simulation Conference indicates that the interest in simulation for modeling health care systems continues to grow, although it may be reaching a convergence point as seen in Figure 2.

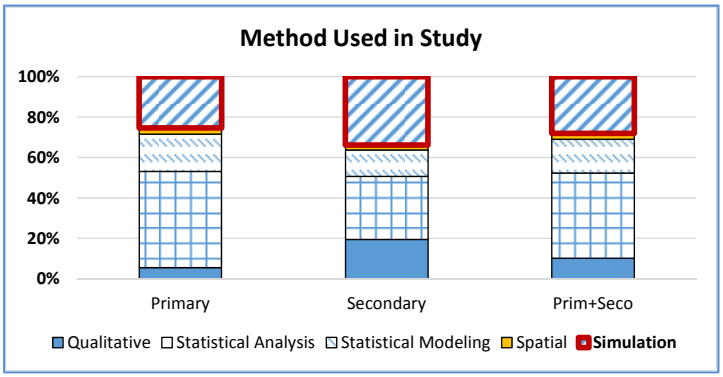

Figure 1: Percentage of articles that used simulation (Based on the findings of Brailsford et al. 2009).

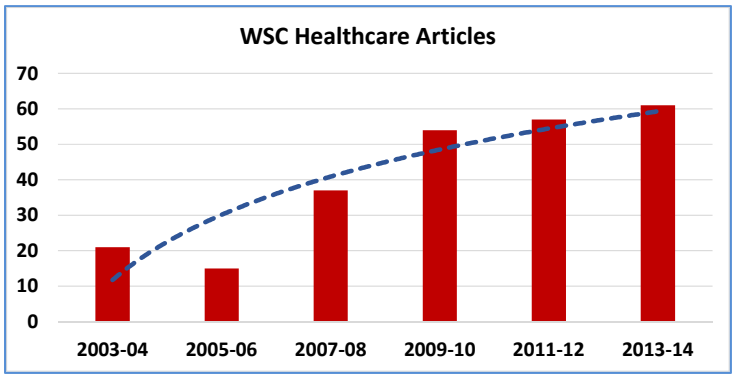

Figure 2: Number of articles published in WinterSim proceedings.

In regards to application areas, different authors have used different criteria to categorize the application areas. For instance, Lowery (1998) used the purpose of the study to identified two broad categories for healthcare applications: analytic decisions and comparison of alternatives. Brailsford et al. (2009) classified articles in four categories: stakeholder interest, clinical and organizational processes, patient care requirements and delivery planning, and research and policy. In our review of the WSC

articles since 2002, we identified five categories: Epidemiology, Operations, Planning/Design, Policy, and Research. Most articles (34%) are focused on simulation studies to improve the *operations* of a hospital subsystem or clinical services as shown in Figure 3. Clearly, discrete event simulation has been extensively used to model healthcare systems, and it is expected that it will continue to be used in the years to come. So let us explore how to use it to model healthcare systems.

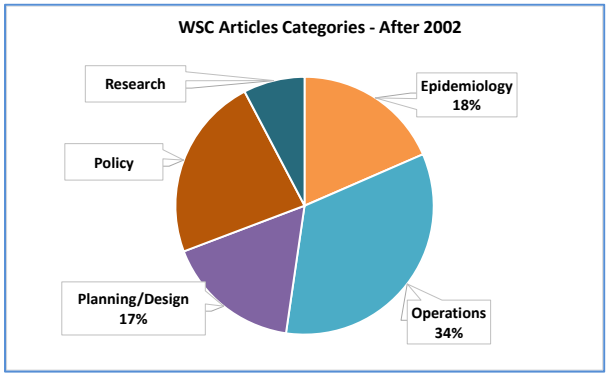

Figure 3: Categories of healthcare articles in WinterSim proceedings.

3 OVERVIEW OF THE SIMULATION MODELING PROCESS

A clarification is needed at this point regarding the words *model* and *simulation*. In the medical field, a model may be the process that a doctor uses to arrive to the treatment needed by a patient, it may be elements and relationships of integrative medicine, or it may be the process to deliver healthcare services (i.e. *patient-centered model*). On the other hand, simulation to a medical professional may imply the set of tools, software and documents to train a doctor or nurse in the diagnostic and treatment of patients.

In the context of this tutorial, *model* refers to a representation of the infrastructure, processes, and resources involved in the delivery of healthcare. On the other hand, *simulation* is a methodology to design and build such models.

3.1 Simulation Modeling

Simulation modeling is a computer-based methodology that enables us to represent real systems and to play *what-if* scenarios, without having to interrupt their operations. With the resulting model, we can "observe" the system under a variety of conditions.

The scope of this article is discrete-event simulation. Hence, from this point forward, the term *simulation* is to be understood as referring to discrete event simulation. Definitions of simulation exists a plenty (Banks et al. 2010; Harrell and Tumay 1995, 1997; Kelton, Sadowski, and Swets 2010). A succinct, yet complete, definition was given by Shannon (1975), and it is still valid today: "*It is the process of designing and building a model of a real system, and conducting experiments with this model for the purpose of understanding the behavior of the system, or of evaluating various strategies for the operation of the system.*"

Simulation modeling for decision making is a *process*. It is not just writing equations and solving them, or entering data into a magic box; rather it is a process, with several phases that must be conducted and completed in a methodic and thorough way. We use such process to *design a model*, based on the objectives of the simulation study. We do not just program the model; we design it by clearly identifying the important components of the health care system to include and establishing appropriate boundaries and assumptions. We must also select the performance indicators to observe (outputs), and define the various conditions (experiments) under which we want to observe those indicators. Once we have a design of the model, we proceed to *build* the model using an appropriate programming language or

simulation package. As part of the model building phase, the model needs to undergo a thorough inspection to ensure that it was done right (verification), and that it does the right things (validation). After verifying and validating the model, it is ready to run the necessary *experiments*. The first thing we seek is to gain understanding of the behavior of the system under current conditions. For instance, we would like to identify bottlenecks in the processing of patients at a clinic or an emergency department (ED). Once the *status quo* has been understood, we can proceed to modify the inputs and operational conditions to explore how the system reacts to different operational scenarios or management strategies. For example, if we realize that the less critical patients in the ED are waiting too long because the beds are occupied, then we may want to explore two changes: 1) adding resources (in this case beds), or 2) implementing a *fast-track* policy with the existing resources.

3.2 The DBE framework of the SMP

Different authors have given slightly different versions of the simulation modeling process (SMP) (Centeno 1996; Banks and Gibson 1998; Leemis and Park 2006; Banks et al. 2010). Conceptually, the SMP may be broken down into three phases (DBE) as shown in Figure 4.

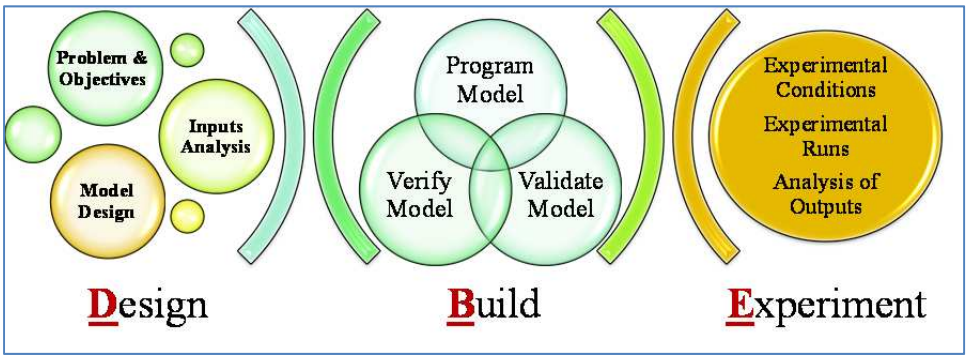

Figure 4: Phases in the simulation modeling process.

1. *Design*: A simulation model has to be designed based on a specific set of objectives. These objectives will dictate the complexity of the model, what type of data will be needed to establish the inputs to the simulation model, as well as the measures of performance of interest and the experimental conditions to be explored with the model. As suggested by Lowery (1996), a good "*rule of thumb is to develop as simple a model as possible*" in order to "*to meet project's immediate objectives*."
2. *Build*: The model is usually built using a simulation package; however, it is possible to build it using any high level programming language, with the appropriate simulation modeling subroutines. If the decision is to use a simulation package, the selection of the package is biased by the experience of the simulation practitioner and by the packages' capabilities to model the system under study. Some of the most popular packages are Simio (www.simio.com), MedModel (www.promodel.com/Products/MedModel/), FlexSim (www.flexsim.com), and ARENA (www.arenasimulation.com). Building the model has perhaps become the easier part of the effort because there is significant modeling capabilities in each one of these packages. Regardless of which package is used, the model must be verified and validated.
3. *Experiment*: The simulation model enables experimentation with "the system." In the real world, a system has inputs or factors that are necessary for the system to operate, and it has outputs or responses that indicate how the system performs. For example, an Emergency Department has as inputs number of beds available, number of nurses and doctors on duty, among others. On the

other hand, its outputs may be wait time, utilization of bed, throughput, or utilization nurses (see Figure 5). For the experimentation phase, it is necessary to decide what inputs to manipulate and what responses to observed. The simulation model will let us "see" how the system responds to specific values or levels of the inputs. It is important to emphasize that a great advantage of using simulation as an experimental tool is that we can include and manipulate certain inputs that in reality we may not control. An example of these inputs is the demand level. In the simulated world, we can vary this factor to establish effective plans to manage resources under various assumed demand levels.

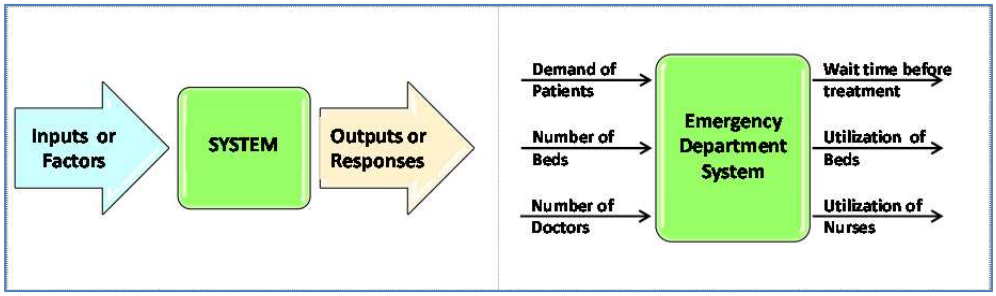

Figure 5: A diagram of a general system.

4 THINKING ABOUT YOUR HEALTHCARE SYSTEM

Understanding any healthcare delivery system or subsystem in a single step is impossible. Thus, we use *functional decomposition* to break down the system into its smaller components and processes (Whitten and Bentley 2007). For instance, a healthcare system (say a hospital) has a subsystem for the emergency department, another for the operating rooms, another for clinics, and it may have one or more ancillary departments, e.g. X-ray department (Figure 6). Attempting to "fix" all the problems in the hospital with a single simulation model is unthinkable!

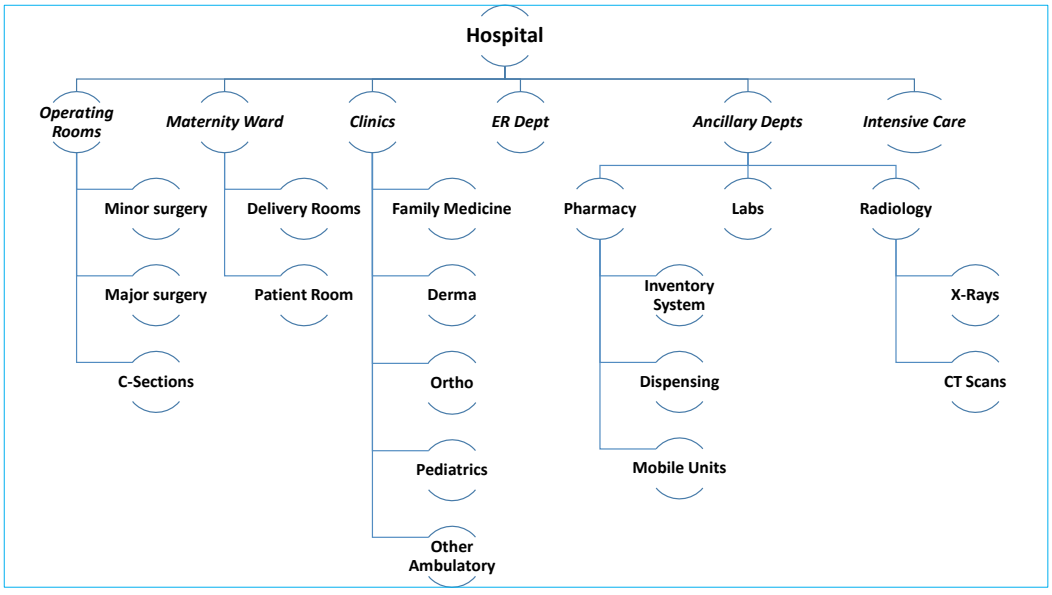

Figure 6: A generic sample hospital system.

Therefore, the first step in using this methodology is to clearly identify the system or subsystem and the problem that we want to fix. For instance, you may want to increase the quality of service (QoS) in the ED. *What are the most prominent problems or suspects that have you believing that the QoS is not up to expectations?* Perhaps a post-treatment survey is telling you that your patients (clients) had to wait a long time, and that in fact, some of them left without being served (LWBS = *reneging*). Then you may set the objectives of a simulation study to be *reduce patient wait time by X%*, or *95% of the patients wait less that X minutes to be seen by doctor*, or *reduce the % of LWBS patient to less than X%*. Clarity on the problem and the objectives will lead to a successful study. Many a times, medical professionals may expect a simulation study to solve more than it is designed for. *Simulation modeling is not a magic wand!* It yields a model that serves as a laboratory where we can play the "*what-if*" game. Suppose that one of the problematic issues is lack of courtesy by the janitorial staff in the waiting area of the ED. You may want to ask: *what if we train janitors on customer relations?* Well, unless you included the janitorial staff in the model *and* a human behavior sub model to tell us about the reaction of janitors to training, the simulation model will not be able to answer such question.

4.1 An Example

This example is a compressed version of a study done by Centeno et al. (2010) of an Endoscopy Clinic. The system has seven rooms, where single or combined procedures are performed (Table 1). The working schedule allows for 98 times slots among all 7 rooms. The facility operates as 100% appointment facility, in other words, no walk-ins are allowed. The scheduling policies do allow for changes up to the previous day of the procedure; however, the procedures should preferably be scheduled at least 3 days in advance. Time slot availability for actual procedures is based on a block schedule for the 22 doctors that the Center works with. Historical records were used to determine the duration of each procedure type. Similarly, the nurses (RNs) and the registrations clerks also vary throughout the day according to a schedule (Table 1).

Table 1: Procedures and resources data.

Procedures			**Resources**			
Type	Description	%	Type	Available	Type	Available
COL	Colonoscopy	56.3%	Doctors	2 to 7	Pre/Post Beds	20
GST	Gastroscopy	18.4%	RN	1 to 12	Recovery Chairs	4
C/G/E	Colon/Gastro	24.3%	Anesthesiologist	2	Registrars	1 to 4
G/F	Gastro/Flex Sig	1.0%	Greeters	1	Rooms	7

Once a patient is referred by a physician, a schedule time and date is set by the scheduler. The patient then goes through a pre-assessment activity to capture personal information. Some of the patients also undergo a pre-registration activity to capture all medical and insurance information. On the day of the surgery, the patient is expected to arrive to the facility 1 hour prior to the actual procedure so that it can go through registration and pre-op activities in a timely fashion. Patients are also expected to arrive with a companion, or to have made arrangements to have someone pick them up after the procedure has been completed, as they are not yet in condition to drive. When they arrive, the patient is greeted by the Director of First Impressions. This individual is in charge of three things: 1) checking that indeed the patient has arrived on the correct day, 2) routing the patient to the next step, and 3) ensuring that the work load in the registration area is relatively balanced. Once a patient has been properly registered, a nurse will come for the patient as soon as a Pre/Post Op Bed is available. Once at the bed, the RN completes the pre-op activities and notifies anesthesiologist and doctor that the patient is ready for the procedure. The duration of the procedure depends on the nature of the procedure itself. Upon completion of the procedure, the anesthesiologist returns the patient to the Pre/Post Op bed area, where the RN is in charge

of the patient until the patient recovers from the anesthesia. Then, the patient is discharged if, and only if, the patient's relative is on-site; otherwise, the patient is transferred to one of the alternate recovery chairs to wait for the patient's relative.

4.2 Problem and Objectives

After several meetings with the appropriate stakeholders, it was clear that the main problem was *low throughput*. Hence, the main objective was to find the necessary mix of resources and scheduling policy to attain a throughput of at least 80 patients per day (vs the existing one of 54). In other words, the objective was to identify what was needed to increase throughput by 48%. Three basic questions needed answers:

1. What are the bottlenecks in the process?
2. How many additional nurses are needed to process 80 patients per day?
3. How bad is the problem of cancellations and no shows?

These questions were the result of pre-conceived suspicions that management had about what was causing the problem. For starters, it was suspected that the registration process was causing delays (bottleneck), it was suspected that there were insufficient nurses to have patients ready, and the last main suspect was that patients were cancelling their appointments.

4.3 Designing the Model

With a clear "destination", the journey to have a simulation model gains traction and speeds up. Two ingredients are paramount to achieve success: 1) Have a hospital or clinic champion, and 2) Use a systems thinking approach. A champion is someone who is enthusiastic about the project, who will carry the flag to upper management, and who will serve as enabler to gain access to data and information. Systems thinking requires explicit identification and definition of the dynamic relationships among the system components. Therefore, we must look at components, processes, and policies that dictate and constrain how patients move within the system and how the staff, nurses, and doctors provide services.

The subsystem to model needs to be visualized. The owners of the system will be quite familiar with it, but if you are a consultant, you may need a tour and a sketch of the system. For our example, a sketch implemented in ARENA is given in Figure 7. The sketch should reflect only the elements that will be included in the simulation. Embellishments are needed only in as much as to facilitate the credibility and confidence on the model.

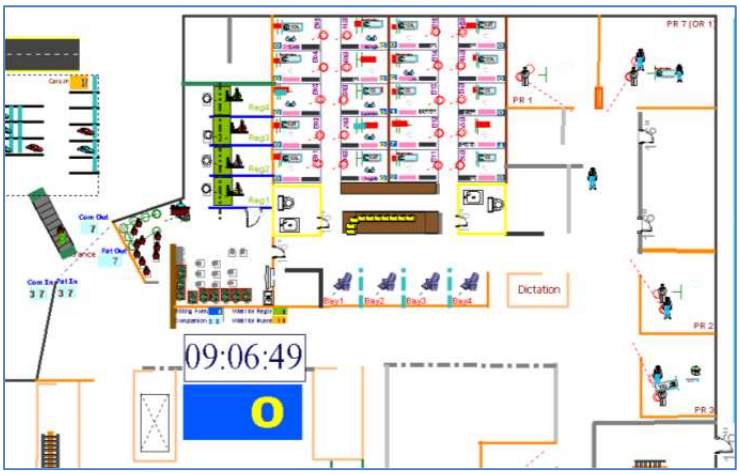

Figure 7: Sketch of endoscopy clinic example.

In addition to the sketch, a flowchart of the various processes always facilitates the understanding of what is happening in the system (see Figure 8). Furthermore, it will lead to a clear understanding of where services take place (Figure 9a), what type of services, who give the services, and who receives such service. Notice in Figure 9b that patients are decomposed into categories depending on the type of procedure they need. The level of detail was needed up to the second level only. Two of the categories in level 3 have very low percentages and we were not interested in distinguishing between these procedures; hence, they were grouped. On the other hand, G/F procedures were kept as a separate category because management was really interested in obtaining statistics about them.

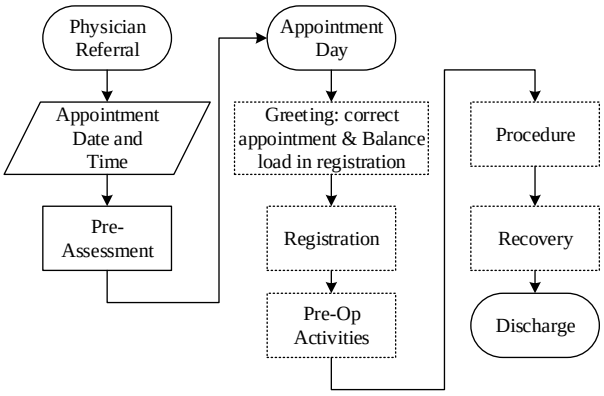

Figure 8: Patient's macro level flow.

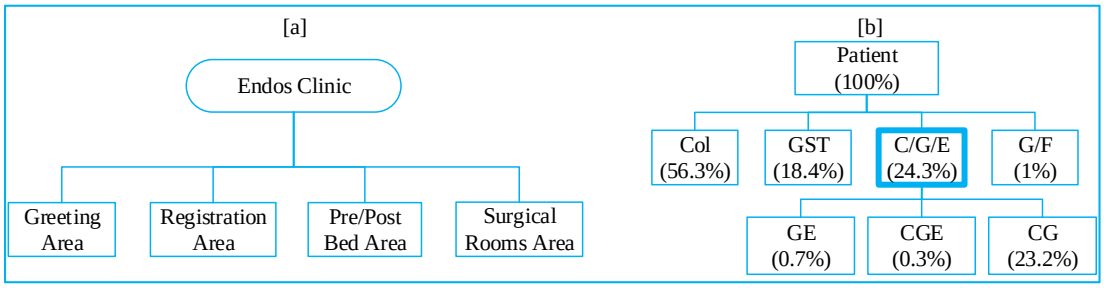

Figure 9: Service areas and patient decomposition.

4.4 Discussion

4.4.1 About the inputs

Despite the widespread use of simulation for modeling health care systems, since the work by Levine (1969), a persistent challenge has been *data*. There are three dimensions to this challenge: quantity, quality, and relevance. For the example, we needed Schedules (Physicians, Registrars, Nurses, Techs), duration of surgical procedure, registration times, depending on whether they had been pre-registered or not, turnaround times for the surgical rooms, behavior patient's arrival in regards to cancellations, no shows, early and late arrivals, appointments per time slot, among others. Although the clinic had records, they did not have full access to them, nor did they have relevant data. Table 2 summarizes the sources of data and some issues found during the study of the example.

The small data sets presented a challenge from the statistical point of view. On several items, we had to use user-defined functions to model the activities' duration. So, the lesson here is that if you are thinking about using simulation for your department, then set up a robust data collection system while you get all the necessary approvals for your study.

A second lesson that we would like to share is that the statistical analysis done to establish inputs is likely to shed light on the real root of the problem or point towards new problems altogether. In the case of the clinic, two of the suspects for the low throughput were the cancellation of appointments and no-shows; however, when we did the data analysis, we discovered that 96% of the patients were actually keeping their appointments, with the remaining 4% being cancellations or no shows (Figure 10a). But that 4% is about 2 patients per day; hence, cancellations and no-shows were not the causes of the low throughput. Furthermore, when we examined the early and late arrivals, we noticed that 78% of the patients arrived early (Figure 10b). You may think this is a good thing; however, an early arrival is likely to be processed out of order, causing the on-time patient to be held back for a lack of bed. This type of delayed began occurring early in the day, and it propagated throughout the day. The registrars and nurses thought that seeing the patients early as a sign of good service. A message we want you to take with you: conduct (or demand) a thorough statistical analysis of the existing data, conduct (or demand) rigorous time studies, and be open minded about the root causes of the problems and to the possibility of the existence of problems you never suspected.

Table 2: Sources of data for the endoscopy clinic example.

Source	Issues
• The center's information system: "patient tracking".	• Only used internally to know where the patient is at any given point in time and to generate performance and tracking reports. • Staff found it difficult to enter accurate starting and ending times for the activities as the boundaries of each activity where understood slightly different by each person.
• Manual logs.	• Not a systemic activity. Log records were initiated by the head nurse on an ad-hoc basis. • Paper based, and data inconsistently captured. • Complete data and commentary only for some patients. • Illegible handwriting rendered some records useless. • Pages are not kept permanently. Data available only cover a small delta *t* (about 1 month).
• Direct observations.	• There were some difficulties conducting the time studies of the surgical procedures. • Data obtained covers a short period of time.

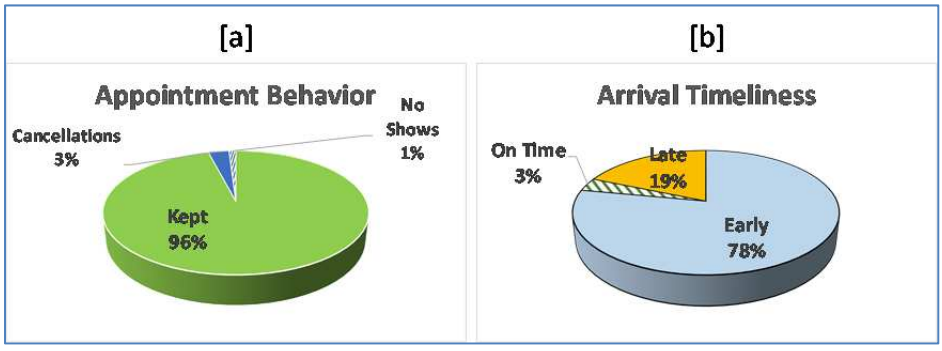

Figure 12: Appointment behavior.

A message we want you to take with you: conduct (or demand) a thorough statistical analysis of the existing data, conduct (or demand) rigorous time studies if needed, and be open minded about the root causes of the problems and to the existence of problems you never suspected.

4.4.2 About the outputs

Simulation modeling per se is not an optimization technique. Nowadays, the simulation packages provide significant support in the experimentation and some for the analysis. A common approach for the experimentation is the factorial design, full or fractional. In the case of the example seven factors were considered, with two to four levels each as shown in Table 3. Based on this, the full factorial experiment has 576 different scenarios. Based on our results from the model of the *status-quo*, and with the agreement of management, we only ran a fractional factorial design, consisting of a subset of 10 scenarios. Each scenario was run for 30 replications. The selected subset requires the scheduling of 80 patients per day, except the first one, which represents the status quo.

Table 3: Experiments for the endoscopy clinic example.

Factor	**Levels**			
	A	**B**	**C**	**D**
Scheduling Rule	Random (0 to 7)	Constant (5/slot)	Varying constant Slots: 1-2 | 3-6 | 7-10 | 11-14 | 15-16 #: 4 | 5 | 6 | 5 | 4	
RN Schedule	As-is	shift down 15 min	shift down 30 min & add 0.2 RN FTE	shift down 30 min & add 1.5 RN FTE
DR Schedule	As-is	Add doctors Slots: 1 | 2-12 | 13 | 14-16 Doctors: +1 | +0 | +1 | +0		
Pre-Admit	No	Yes (50%)	Yes (75%)	
Beds	20	24		
Room Assignment	As-is	Random		
Discharge Time	As-is	Reduce by 25%		

The meaning of these factors is as follows:

1. *Scheduling Rule*: This factor is used to vary the number of appointments to generate per time slot. The number of appointments is independent from time slot to time slot. There are 16 time slots per day. Prior to the study, some time slots could be fully filled (7 patients), whereas others would be empty or only have a couple of patients. An alternative was to have 5 patients scheduled per time slot, uniformly throughout the day. A second alternative was to have less patient in the time slot at the beginning and the end of the day, and more patients in the time slots in the middle of the day. Under both alternatives, there would be 80 patients processed.
2. *RN Schedule*: We explored three alternatives to the current schedule. The first one involved shifting down the current schedule by 15 min to have more RNs at the beginning of the day. The schedule of the doctors starts 1 hour after that of the registrars' and RNs'. The other two are a combination of shifting down the schedule and adding additional RN full time equivalences (FTEs).
3. *Dr Schedule*: One alternative was explored, namely shifting the schedule of some doctors such that there are 2 additional doctors at the beginning of the day. Historic records, observations, and the simulation of the "*as-is*" system clearly showed that the backlog begins to form around 7 AM when the clinic is not yet working at full speed.
4. *Pre Admit*: Management was interested in checking to see if they should pre admit patients or not. By doing this, the pre-op time would be reduced. Management and nurses estimated that the impact could be as low as 50% and as high as 75% reduction of the pre-op time.

5. *Beds*: One alternative considered was the conversion of the alternate recovery chairs into permanent pre/post op beds.
6. *Room Assignment*: We explored if the rooms and doctors' utilization would improve by assigning the rooms as the rooms became available, breaking ties randomly. This option was based the statistical analysis to establish inputs. We noticed that, in some instances, patients were forced to wait for their procedure even though there was a room available. The reason given to us by the staff was that the doctors had a "favorite" room, even though the rooms had the same equipment and were basically the same.
7. *Discharge Time*: Doctor use anesthesia at their own discretion and preference. So, we explored the option of doctors using the same, medically acceptable, standard on the application of anesthesia. It was estimated by the doctors that the discharge time could be reduced by up to 25%.

The type of analysis to do must be aligned to meet the objectives and answered the questions of the study: *Do you do a means analysis?* Or *do you do* a *percentile analysis?* The type of analysis to be done must be discussed with the stakeholders from the moment that the objectives of the study are set, and the topic should be revisited again at the beginning of the experimentation. This is a critical step because it enables the simulation practitioner to communicate what the healthcare system owner should expect at the end of the study. Furthermore, the concept of *experimentation* must be explained as many times as needed to ensure that the stakeholders expectations are not set irrationally high. One of the best-selling points of the simulation methodology is that it gives us the ability to assess multiple parameters simultaneously, even if they conflict with each other.

Finally, when looking at the results of the analysis, you must look at them with open eyes and open mind. Look for answers beyond those you anticipated. For example, in the case of the clinic, one of the suspected bottlenecks was the registration process. However, when we looked at the results for waiting times and utilizations, we realized that the registration process had almost no bearing on the total flow time, nor on throughput. Rather, the two factors that had the most impact were the policy to assign the room for the procedure and the RN availability. Of these two factors, the room assignment policy was the one with the most impact. As an alternative to this policy, we used the simulation model to test the idea to assign the first available room; in other words, to ignore the doctor's preferences. The results were stunning because the wait time for a room reduced by almost half. In addition, we were also able to see that registration could not be blamed for the low throughput. In the end, the 48% increase in throughput could be achieved by assigning the first available room, shifting the schedule of 1 nurse 30 minutes earlier, adding 1.5 FTE of RN, and scheduling 5 appointments per time slot, leaving a slack of 2 appointments for emergencies.

A message we want you to take with you is: *exercise judicious care when setting up the experiments*. If you are the stakeholder, not the analyst, be actively engaged in the design of the model and experiments to ensure that your questions are answered. Conduct (or demand) a thorough statistical analysis of the results of the various experiments, and be inquisitive about what the results say regarding the performance of your healthcare system.

5 SOME CHALLENGES

Although simulation modeling is an appropriate and versatile tool to evaluate alternatives and find solutions to many of the problems found in healthcare systems, "*many*" is not the same as "*all*". Hence, remember that there may be a need for several simulation studies, and that the result of these studies needs to combine with other knowledge to reach robust decisions. Table 4 gives a summary of the deliverables expected out of each one of the three phases of the SMP, and the skill set needed.

Another challenge for using simulation modeling is that it needs *relevant* data. Without relevant data, the value of the results is questionable. The main issue that we have observed is that existing relevant data

tend to be few, despite the extensive databases that healthcare systems have. The quality of informal data collection is spotty, and the preservation of the data tends to be non-existent. Managers of healthcare systems need to put in place better data collection systems, so that a variety of models can be developed to understand and evaluate these systems. We need large quantities of *relevant* metrics to adequately establish inputs for the simulation models.

Table 4: Summary of deliverables for the DBE phases.

	STEP	DELIVERABLES	SKILLS SET
Design	Problem definition	• A concise and complete problem statement. • A sketch of the system, a flowchart. • General description of the system, including operating policies and constraints. • Cause-and-effect diagrams.	Project management, communication, people skills, facts synthesis.
	Objectives definition	• List of specific objectives. • Statement of the scope. • Gantt chart of project's activities.	Project management, communication.
	Data acquisition	• A series of data sets. • Ratification of the objectives and of the scope of the project.	Fact-finding, data manipulation, communication.
	Data preparation & analysis	• Data sets ready to be analyzed. • Probability functions (or data) modeling the various activities in the system.	Data manipulation, statistical analysis, Software skills.
	Model Design	• Documentation on the objects that will be included in the simulation model. • Documentation of the various experiments to run; inputs to change, measures to observe.	Project management, design skills, Communication.
Build	Build	• A model in a simulation package or high level programming language. • Documentation for the model.	Programming, writing skills.
	Verify	• A model that runs with no errors.	Programming, team skills.
	Validate	• A model that represents the real system.	Programming, team skills, statistical analysis.
Experimentation	Experimental Design	• A comprehensive design of experiment.	Statistical analysis.
	Experimentation	• A set of observations for each measure of performance, for each alternative.	Programming, organizational skills.
	Analysis of Outputs	• A detailed analysis of the measures of performance across alternatives.	Statistical analysis.
	Documentation	• A final report.	Writing skills.
	Implementation	• A recommendation to improve the system.	Project Management.

Another challenge is the skill set needed to conduct a simulation study. For the healthcare system administrator this may imply acquiring new knowledge, or choosing to use a consultant. But, at the very least, administrators need to have a basic knowledge of what can be done with statistics and simulation to participate actively and to ask informed questions. It is worth emphasizing the distinction between "*data manipulation*" and "*statistical analysis*" skills. The former refers to skills needed to extract data from

databases (e.g. knowledge of SQL), to scan or format data collected via time studies, and to screen and group large data sets into smaller sets (Excel's tables, pivoting, etc.). On the other hand, the latter refers to skills to conduct descriptive and inferential analysis.

6 SUMMARY

Healthcare systems are highly dynamic, not only in the stochastic nature of their processes and Healthcare systems are highly dynamic, not only because of the stochastic nature of their processes and relationships, but also in their governing policies and procedures. The need to control costs, while increasing access and QoS is demanding that healthcare administrators use more comprehensive and flexible tools. Discrete event simulation has proven to be effective. However, the main handicap of it is that simulation studies require data, and relevant data are typically difficult to acquire.

Newer versions of simulation packages are providing more and more modeling capability to represent the intricate relationships found in healthcare systems. Software continues to advance to give us more and better representation capabilities. Likewise, simulation methodologies continue to evolve and new one are being developed. Two methodologies that have begun to make significant contributions to modeling healthcare systems are Agent-Based Simulation (ABS) and Risk-based Planning and Scheduling (RPS).

ABS is a modeling framework in which we can model complex systems dynamics that include autonomous entities. These entities, called *agents*, move through the system displaying independent behaviors (Macal and North 2014). Some examples of the application of ABS are found in disease spread modeling (Aleman, Wibisono, and Schwartz 2009; Parker and Epstein 2011) and pharmaceutical research (Hunt et al. 2013).

RPS generates a resource constrained deterministic schedule and a probabilistic risk analysis of such schedule to account for possible variations, and RPS does it using the same simulation model (Kelton, Smith, and Sturrock 2014). RPS yields the schedule by running the model under deterministic and ideal conditions; then, a switch is turn on to activate stochastic behavior of the system and to see how the schedule stands up to such behaviors. Appropriate risks measures are generated, including the probability of meeting a desire target.

These advances in software, combined with advances in simulation methodologies, will continue to add capability and flexibility, so that we can build more reliable and detailed models of healthcare systems.

Summarizing, simulation is a flexible methodology that enables *what-if* experimentation. As you embrace simulation as one of your tools for analysis and decision making, keep in mind the following observations:

- Securing a champion for the simulation project tends to ease access to people, data, and information.
- Setting up an appropriate data collection mechanism will help reduce the challenges regarding the availability and reliability of relevant data.
- Defining clear and feasible scope and objectives will keep stakeholders' expectation reasonable.
- Using a variety of graphical tools facilitates gaining an understanding of the components and relationships of the healthcare system.
- New problems, or new causes for existing problems, may be discovered during the statistical analysis of inputs and outputs.
- On-going research may give us better methods and tools to model healthcare systems.

Lastly, attending conferences, such as the winter simulation conference, is a good way to keep abreast of what is new to model healthcare systems.

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