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## SIMULATION ANALYSIS IMPROVES OPERATIONS AT EMERGENCY DEPARTMENT AND SURGICAL SUITE

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### **KEYWORDS**

Emergency department, surgical suite, discrete-event process simulation, health care.

#### ABSTRACT

Discrete-event simulation now has a long and distinguished track record of guiding improvements to queueing systems subject to severe operational and budget constraints and also held to lofty expectations of service speed and quality. Historically, this track record began with simulation applications to manufacturing operations. These applications have now expanded far beyond manufacturing plants, to include supply-chain distribution systems, transport terminals, service industries (e.g., hotels and restaurants), and health care delivery in hospitals, clinics, and doctors' and dentists' offices.

Relative to the application of discrete-event simulation discussed in this paper, a large medical center in the Midwest region of the United States availed itself of the ability of simulation to guide improvements to and expansion of the emergency department and the surgical suite over a planning horizon of nearly a decade. This medical center serves a large urban area and the surrounding rural areas, and anticipates considerable pressure of increasing demand for its services. This increasing demand is attributable to significant demographic trends such as increasing density of population and gradually increasing average age of this population.

### INTRODUCTION

During the last half-century, discrete-event process simulation has made enormous contributions to productivity, efficiency, and economic viability of a wide variety of activities in many economic sectors. Historically, the first, and still many of the most conspicuous, such contributions pertained to manufacturing, whether in large assembly plants or "custom-order" job shops; example applications abound in the literature. More recently, simulation has been used extensively in service industries (e.g. restaurants), government operations (e.g., courthouses), supply chain operations (e.g., configuration

and operation of warehouses), and the health care industry. In the health care industry, simulation is making high-value contributions to the configuration, staffing, and operation of hospitals, clinics, long-term care centers, and private medical practices. For example, (Baskaran, Bargiela, and Qu 2013) and (Yankovic and Green 2011) applied simulation to the cost-effective scheduling of nurses, thereby addressing the chronic shortages and high costs of skilled nurses. Discrete-event simulation was used to analyze and improve the performance of a hospital blood laboratory, as documented in (Kadı, Kuvvetli, and Colak 2016). Recently, (Zhang, Hanchi, and Meijer 2017) used simulation to identify the factors most heavily influencing the length of patients' stays in a surgery center, thereby improving the reliability of scheduling. As an example of planning for most unwelcome contingencies, (Zehrouni et al. 2017) describes the use of simulation to propose a viable emergency plan in case of a major flood in the region a hospital serves - disasters simultaneously increase demand for emergency services and impede provision of them.

In the present study, which covered a *much* longer time horizon than most simulation studies in either health care or manufacturing, managers and analysts at a large medical center in the Midwest region of the United States sought simulation guidance and predictive analytics for their emergency department and surgical suite - and the interrelationships between them. Patients initially entering the emergency department often proceed to surgery after doctors stabilize their medical condition. Therefore, two simulation models were built and analyzed – one for the emergency department and one for the surgical suite – and the outputs of these models were analyzed concurrently. Due to demographic trends, management of the medical center is confident that demand for services will increase steadily and significantly through a planning horizon ending in 2024. These managers looked to simulation to guide decisions on expansion plans and choices of operational procedures.

The remainder of this paper is organized as follows: The next section describes, at a high level, the operations at the medical center, particularly the emergency department and the surgical suite. The following two sections explain the steps undertaken to analyze the input data and to build, verify, and validate the model. Then we present highlights of the results and indicate likely directions of future work.

### **OVERVIEW OF OPERATIONS**

The regional medical center serves residents of parts of three midwestern states. Further, by providing an air-ambulance service, it can and does provide lifesaving emergency service to rural and farming regions nearby. The simulation study described in this paper, at the client's request, concentrated on two of the largest and most vital components of the medical center: The emergency department and the surgical suite. A key objective of the study was to provide advice to upper management on how to best ensure support of projected increased patient volumes through 2024. The emergency department, as is typical, must address urgent issues of trauma (e.g., automobile accidents), cardiac emergencies (e.g., heart attack), chest pain (e.g., pneumonia), and many others, as described in (Rossetti, Trzcinski, and Syverud 1999). The surgical suite, comprising multiple operating rooms, has similar complex operational and staffing concerns, similar to those described in (Lowery and Davis 1999). One of the operating rooms is designated as cardiovascular - and reserved for that type of surgery only. Furthermore, at least one operating room within the surgical suite must always be available (if not indeed in actual use!) for a suddenly arising emergency surgery. The surgical suite also includes the post-anesthesia care unit [PACU].

### INPUT DATA AND ITS ANALYSIS

Extensive input data from medical center records, encompassing the calendar year 2016, was made available to the simulation analysts. For the emergency department, these data included arrival time, medical problem presented, the extent of services required (time devoted to the patient by nurse(s) and doctor(s), and any other services such as Xrays), and the disposition of the patient (i.e., to home, to a private doctor, or into a hospital, or into the medical center surgery center. For the surgical suite, these data included date and time, operation performed, operating room used, time spent by surgeons, anesthesiologists, and nurses, and time the patient subsequently spent in the PACU. These data were entered into Microsoft Excel® workbooks and thence read into the respective Simio® models. Examples of these data tables, as provided by the clients, are shown in the Appendix (Figure 1 and Figure 2). Therefore, in this project, there was no need to fit closed-form probability distributions to input data sets (Law 2016).

Additionally, the medical center documented standard operational procedures, such as the typical routes traveled by and services received by various types of patients. For example, the emergency department of course operated continuously, 24 hours a day, 7 days a week. Except for emergency surgeries, the operating rooms within the surgical suite operated 7AM to 5PM Mondays, Wednesdays, and Fridays, with slightly reduced hours (7AM-3PM Tuesdays and Thursdays). Particularly for the surgical suite model, preliminary analysis with Microsoft Excel® (including macros) derived key information such as the proper proportional allocation of patients to type of surgery and length of stay for the various types of surgery.

# MODEL CONSTRUCTION, VERIFICATION, AND VALIDATION

After discussion of more than half a dozen alternatives (there are many as documented in (Abu-Taieh, Evon M. O. and Asim Abdel Rahman El Sheikh 2007)) between the clients and the simulation analysts, the well-known simulation software Simio [SIMulation using Intelligent Objects], known to several client engineers via their university studies, was selected for construction of the two simulation models. This software provides ease of use, high modeling power, easy specification of extensive experimentation to compare scenarios, and high-quality animation (Joines and Roberts 2015).

For the emergency department model, typical hourly demand curves for each day of the week were constructed, based upon the historical 2016 data. Lengths of stay were calculated as a range for each patient type and modeled as a triangular distribution. The clients specifically requested that the triangular distribution be used, and this request was deemed reasonable based on histograms of the pertinent data set. Likewise, for the surgical suite model, the year-2016 case volumes and turnaround times, subclassified by patient type and surgical specialty, were scheduled across each day of the week within the model. Post-surgery dwell times in the PACU were incorporated into this model similarly.

Various well-known methods of verification and validation were used (Sargent 2013). These included directional analyses (if arrival rate increases, do queue lengths increase?), examination of the animation, and allowing only one entity (patient) to enter the model and examining the path it takes. Very importantly, in view of the unusually extensive historical data available, both models were run "with yesterday's data." Simio® provides a valuable feature called an "arrival table," allowing convenient specification of arrivals according to a historical logbook (Smith, Sturrock, and Kelton 2017).

Since validation included having the models precisely (within 3%) duplicate "yesterday's observed historical results," both models very quickly achieved high credibility with the clients. This credibility was also enhanced by realistic, yet not overelaborate, animations. Next, each model was run for one year (indeed, as in the (Kadı, Kuvvetli, and Çolak 2016) study) to obtain key performance metrics, including queue lengths, queue residence times, resource utilizations, and total patients served. In lieu of specifying a warm-up period (the usual procedure when modeling a steady-state system such as this medical center, in contrast to a terminating system such as a bank or retail store) (Robinson 2014), the analyst, using the extensive historical data available, captured the times of entry and exit into each service center, and then calculated the service center's utilization.

### **RESULTS OF THE SIMULATION MODEL**

Results reported by the emergency department model included average and maximum times in system and in queue, average and maximum queue lengths, and utilization of resources (both personnel such as doctors, nurses, and aides; and resources of equipment (e.g., X-ray machines). These results were presented both overall and subdivided by time of day and day of week. They were compared for various possible arrival rates, reflecting uncertainty of the increased demand for services during the planning horizon specified in the study.

Results (including the same performance metrics as for the emergency department, plus the percentages of operations starting at the originally scheduled time) obtained from the surgical suite model included comparative simulations with six, seven, and eight operating rooms; each of these scenarios was run with both average (to include both arithmetic mean and median) and third-quartile (75<sup>th</sup> percentile) patient volume demand levels. For each of these scenarios, utilizations of the operating rooms were reported both in aggregate and by day of the week, and further relative to type of operation (e.g., cardiac) performed. Analogous results were reported for the preparatory rooms and the PACU.

### CONCLUSIONS AND FURTHER WORK

Conclusions from this simulation study provided significant reassurances to the client relative to the need for very large capital expenditures, which – if needed – must be undertaken early in the planning horizon. Specifically, relative to the emergency department, the simulation model and analysis of its output confirmed that:

- 1. The medical center will be able to handle projected volumes of patients with the 24 treatment rooms already available and currently underutilized;
- 2. The low utilization of these rooms will assure significant capacity for volume growth without investing in more physical space (the eight hallway rooms were barely used during the simulation runs);
- 3. The current number of employees working in registration and triage will continue to be sufficient throughout the planning horizon.

Relative to the surgical suite, analysis of the model similarly confirmed that:

- 1. The medical center will be able to handle the 2024 projected patient volume with eight operating rooms at 65%-70% utilization;
- 2. Overall capacity can be increased by allowing noncardiovascular cases to be processed in the operating room currently dedicated

"cardiovascular" whenever doing so is medically feasible;

3. The projected number of pre-operation rooms and PACUs will be sufficient to handle projected volume increases through 2024.

Toward the end of this simulation study, on client request, a cursory analysis of the medical center's parking lot capacity was undertaken. Inasmuch as public transport is sorely lacking in the region the hospital serves, almost all patients not arriving by ambulance arrive by private vehicle (very likely driven by a relative or friend). Likewise, these friends and relatives often come to the medical center to visit patients. Very plausibly, future work will include a much more detailed study of this parking lot, its capacity, and the number of parking places needed as "handicapped parking."

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EDWARD WILLIAMS holds bachelor's and master's degrees in mathematics (Michigan State University, 1967; University of Wisconsin, 1968). From 1969 to 1971, he did statistical programming and analysis of biomedical data at Walter Reed Army Hospital, Washington, D.C. He joined Ford Motor Company in 1972, where he worked until retirement in December 2001 as a computer software analyst supporting statistical and simulation software. After retirement from Ford, he joined PMC, Dearborn, Michigan, as a senior simulation analyst. Also, since 1980, he has taught classes at the University of Michigan, including both undergraduate and graduate simulation classes using GPSS/H<sup>TM</sup>, SLAM II<sup>TM</sup>, SIMAN<sup>TM</sup>, ProModel®, SIMUL8®, or Arena®. He is a member of the Institute of Industrial Engineers [IIE], the Society for Computer Simulation International [SCS], and the Michigan Simulation Users Group [MSUG]. He serves on the editorial board of the International Journal of Industrial Engineering – Applications and Practice. During the last several years, he has given invited plenary addresses on simulation and statistics at conferences in Monterrey, México; İstanbul, Turkey; Genova, Italy; Rīga, Latvia; and Jyväskylä, Finland. He served as a co-editor of Proceedings of the International Workshop on Harbour, Maritime and Multimodal Logistics Modelling & Simulation 2003, a conference held in Rīga, Latvia. Likewise, he served the Summer Computer Simulation Conferences of 2004, 2005, and 2006 as Proceedings co-editor. He was the Simulation Applications track coordinator for the 2011 Winter Simulation Conference. A paper he co-authored with three of his simulation students won "best paper in track" award at the Fifth International Conference on Industrial Engineering and Operations Management, held in Dubai, United Arab Emirates, in March 2015. His email addresses are ewilliams@pmcorp.com and williame@umich.edu.

### APPENDIX

Pacility	Process	es h Definitions	21.9 4.32 Data	Results	Plann	ing				
Views	< Patier	nt Arrival Patient Di	istribution Type	e Room In	put Nodes	Hall	lway Input Nodes			
1000000	Bound t	Bound to Excel: C:\Users\gcarreno\Desktop\Page Simulation Models\ED Simulation Model\ED Simulation Model Interface.xlsx, Worksheet: Patie								
1000000		Patient Type Name			LOS Processing Time			Patient Distribution Percentage		
Tables	▶1	ED Patients Admit	Random.Triangular(195,211,231)		1)	18.3458625816937				
	2	ED Patients Admit	Random.Triangular(195,211,231)			1)	3.4944500155607			
	3	ED Discharges			Random.Triangular(117,122,127)			7)	63.0486531346174	
Lookup Table	p Tables 4 ED Discharges - AMB				Random.Triangular(117,122,127)			7)	12.0092672637366	
	5				Random.Triangular(39,58,133)				2.80438466060376	
100	6				Random.Triangular(5,34,70)				0.297382343787821	
Rate Tables	*									
21 Work Schedul										
Input Parameters	2									

Figure 1. One of several Data Tables for the Emergency Department Model

Patier	ntarrival Table Shift Table Surgical Specialty Distibution		Input Node Names F	ailure Shift			
Bound t	to Excel: C:\Users\gcarr	eno≬	Desktop\OR Simulation Model\	OR Simulation Model Interfa	ce.xlsx, Worksheet: InpatientAm	bulatoryDistribution	
	Surgical Specialty		Inpatient Percentage Late	Inpatient Late Avg Time	Ambulatory Percentage Late	Ambulatory Late Avg Time	Monday Inpatient Distribution
1	Cardiac Surgery	0	0.332089552238806	33.1348314606742	2 0.4	93	13.8361805251793
2	Vascular Surgery	0	0.475247524752475	47.9166666666666	0.16666666666666	21	4.01846305252969
3	Thoracic Surgery	0	0.40909090909090909	92.777777777778	0	0	0.542518838307084
4	General Surgery	0	0.262312633832976	47.4938775510204	0.219832735961768	40.0217391304348	34.4983054791038
5	Urology Surgery	0	0.36013986013986	37.5825242718447	0.35555555555555	30.0875	17.1531835429117
6	Orthopedic Surgery	0	0.303630363036304	51.5163043478261	0.344660194174757	34.7746478873239	11.6719766097011
7	Podiatry Surgery	0	0.359712230215827	50.18	0.37037037037037	19.45	5.30239341403437
8	Hand Surgery	0	0.625	23.6	0.548387096774194	24.3529411764706	0.661699036832653
9	Neuro Surgery	0	0.342507645259939	36.9017857142857	0.285714285714286	29.33333333333333	10.4068740411738
10	Spine Surgery	0	0.66666666666666	83.5	; 0	0	C
11	Gynecology Surg	0	0.38333333333333333	15.9565217391304	0.28888888888888888	17.3076923076923	1.132
12	ENT Surgery	0	0.482758620689655	31.7142857142857	0.473684210526316	35.583333333333333	0.289143816785516
13	Ophthalmology S	0	0.25	106	0.285714285714286	11.5	C
14	Dental Surgery	0	0.625	34.5333333333333	0.40909090909090909	32.4444444444444	0
15	Oral Maxillofacial	0	0.285714285714286	15.5	0.24	20.6666666666666	0.163839003310664
16	Plastic Surgery	0	0.5	30.375	i 0	0	0.221840651434228
17	Organ Procurem	0	0	C	0	0	0.10156561201102

Figure 2. One of several Data Tables for the Surgical Suite Model