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The Marginal Utility of Medical Resources in Clinics with Deterministic Patient Arrivals: A Simulation Study

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ABSTRACT

In recent years, dramatic increase in the cost of health care has compelled practitioners to draw a balance between improving efficiency and reducing costs. A discrete-event simulation model has been constructed to assist a typical two-physician family practice healthcare clinic in evaluating potential resource allocations to improve operating efficiencies and patient satisfaction. A performance measure, constructed on a monetary scale (dollars/day), strives to simultaneously satisfy the conflicts of patients, medical staff, and clinic owners by capturing system dynamics. Utility of medical resources is studied from the point of view of a local two-physician nephrology clinic in the light of resource flexibility, resource scheduling, and resource allocation to arrive at an 'efficient utility frontier', a reflection of patient satisfaction.

Keywords

Discrete-event simulation, system dynamics, healthcare, marginal utility, deterministic patient inflow

1. INTRODUCTION

The healthcare profession of the 21st century stands at the crest of a complex dynamic environment that includes aggressive price competition, cutting-edge technological strides, and frequent changes in standards. Since the 1960s, Operations Research (OR) have been successfully used in assisting clinical decision making, facility location and planning, resource allocation, evaluation of treatments, and organizational redesign (Brailsford 2007). Discrete-event simulation (DES) is an effective operational research tool in the hands of health care professionals for allocating available resources to improve patient flow and minimize health care delivery costs, thereby increasing patient satisfaction. While DES is, without doubt, the most widely used simulation approach in healthcare (Davies and Davies 1994), another simulation approach: system dynamics (SD; Brailsford 2008), has been steadily gaining ground in the recent years. This paper draws inspiration from both these simulation methods and attempts to merge the two theories to economics and practice.

Economics is defined as the study of choices made by individuals or group of individuals when resources are limited (O'Sullivan and Sheffrin 2003). This concept of limited resources, better known as *scarcity*, is the backbone of economic thinking. In this context, healthcare is no outlier; Mosby Medical Encyclopedia defines healthcare economics as the study of "supply and demand of healthcare resources[1] and the impact of healthcare resources on a population" (1992). Resource scarcity is an everyday issue in this sector, given the uncertainty and large variance in the demand of healthcare. Under conditions of high constraint and performance expectations, resource efficiency and allocation need special thought. This leads us to the concept and definition of *utility*. Utility is the capacity of a commodity or a service to satisfy some human want (dictionary.com). In healthcare, utility is the satisfaction someone gets from using a product (service provided for good health). The ideal allocation of medical resources epitomizes 'marginal utility', which, in this scenario, refers to the additional satisfaction a patient (and hence the clinic) derives from the consumption of one extra unit of medical resource (Black et al 1973).

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[1] While healthcare resources are three broad categories: medical supplies, personnel, and capital inputs (Santerre and Neun 2000); this paper defines 'medical resources" by lumping the principal human resources (physicians, nurses, and medical assistants) and principal technical resources (exam room, phones, computers, etc.) in a family practice healthcare clinic setting.

Renal Consultants, Inc. is a two-physician family practice healthcare clinic in Canton, OH that specializes in nephrology. Since the patient arrival in this clinic is a function of the appointment schedule set up by the clinic staff, the patient flow is essentially 'deterministic' in nature. The two physicians at this clinic have, in the past, speculated at recruiting a third physician or making any other change in the existing model to increase patient throughput and decrease patient waiting time at the clinic. This paper asks the research question: *What drives utility in a small business medical clinic with deterministic patient flow?* We use Renal Consultants as a case study in this endeavor to further answer (a) Do human resources fare batter than technical resources, i.e. does system dynamics impact the human behavior, and hence, utility? (b) If one form of resource fares better than the other, what is the right mix? And finally, we posit an efficient frontier for medical resource utility in a small business clinic with deterministic patient inflow.

The rest of the paper is organized as follows: section 2 discusses the theoretical background and concerned literature; section 3 details the methodology adopted to conduct the simulation test on the clinic, specifically the scope and layout of the clinic, a schematic of the patient-service flow, input assumptions and building blocks of the model, and finally a dossier on clinic effectiveness; section 4 includes a thorough discussion and analyses on the results; section 5 provides conclusions from the research, as well as directions for future research.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

The choice of simulation methods as *the* Operations Research technique in health care decision making draws inspiration from three reasons. First, healthcare systems are characterized by uncertainty and variability, and hence require a stochastic approach. Second, healthcare systems require a robust modeling approach capable of dealing with complexities. Finally, the key role played by human beings (doctors, nurses, medical assistants, patients) requires a behavioral approach to the modeling where the approach is a dynamically evolved process based on the environment dynamics. While *discrete event simulation* fulfills the first two reasons mentioned above, *system dynamics* takes care of the third. Brailsford (2008) equates SD to Jay Forrester's (1961) seminal work on industrial dynamics and posits the fundamental principle of SD: *structure determines behavior*. A multitude of factors (patient inflow pattern, level of ailment, knowledge of patient condition, et al) define system dynamics in a clinic setup (*structure*). Renal Consultants, Inc. has its unique 'system dynamics' within which its medical resources operate (*behave*).

Since the early articles on simulation studies in individual health care clinics (Bailey 1952; Fetter and Thompson 1965), several other researchers have used simulation models on outpatient clinics to address problems in clinic queuing, clinic staffing, and patient flow (Rising et al 1973; Hancock and Walter 1979; Swisher et al 2001). Jun et al (1999) provides a complete taxonomy of the literature in simulation of single and multi-facility healthcare clinics. The typical utilization of simulation till that time was to find causality between patient throughput and scheduling; in other words, patient throughput dictated clinic profit. The next wave of research in this area aimed at incorporating the effect of patient and physician satisfaction into the clinic profit structure (Ho and Lau 1992; Swisher and Jacobson 2002; Davies 2006; Ferrin et al 2007; Takakuwa and Wijewickrama 2008).

This paper seeks to zero in on the decision making aspect and provides a rationale to decision makers of small-business clinics to structure the right blend of medical resources, thereby maximizing profitability and patient satisfaction.

3. METHODOLOGY

To assist Renal Consultants, Inc. in evaluating clinic performance and effectiveness, a discrete-event simulation model is developed using ARENA (Arena 2009). This section is arranged as follows: subsection 3.1 explains the current layout and scope of the clinic, with responsibilities of medical resources as regards to the patient-service flow; subsection 3.2 discusses the input assumptions and building blocks of the simulation model for the clinic; finally subsection 3.3 elaborates on a univariate performance measure to define clinic effectiveness.

3.1 Clinic Layout

Renal Consultants, Inc. is a two-physician family specialty (nephrology) clinic that currently houses two physicians, three medical assistants, two examination rooms, one waiting room with provision to sit eight individuals at a time, and a refreshment area for the clinic staff (figure 1). Owners of the clinic suggest that the facility is capable of adjusting its layout to accommodate one more physician, another exam room, one more medical assistant and another telephone line. Before a discussion on the operational side of the clinic, it is worthwhile to mention that Nephrology is the branch of internal medicine that deals with the function and diseases in the kidney. Patients frequenting this clinic are typically in their mid 50s, either with beginning stages of kidney malfunction, or with a case of dialysis, or worse, waiting for a kidney transplant.

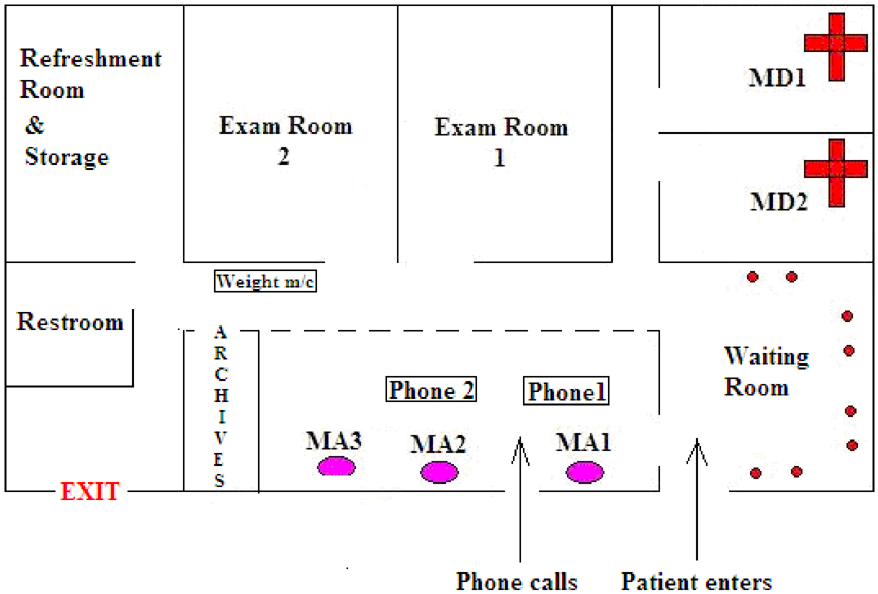

Figure 1. Current Clinic Layout

The clinic operates from Monday through Friday, 9:00AM till 5:00PM, with a one hour lunch break from Noon-1:00PM. All patients enter based on a prior appointment schedule set up by the clinic staff, i.e. this clinic does not entertain walk-ins. Since this medical specialty deals mostly with elderly people, some patients have companions assisting them in their trip to the clinic. However, since the entry of patients to the clinic is restricted by the appointment schedule chartered by the clinic staff, we slack the assumption of 'an overflow in the waiting area' in this research; hence any 'companion' effect is unaccounted for in the simulation. In the rest of the paper, we will refer to the three medical assistants as 'MA' with subscripts 1, 2, and 3, respectively; the two physicians as 'DOC' with subscripts 1 and 2, respectively; the two examination rooms as 'ER' with subscripts 1 and 2, respectively; and finally, the two telephone lines as Phone 1 and Phone 2, respectively.

Phone 1 is used for both incoming and outgoing phone calls that deal with appointments for new patients (incoming calls) and confirmation of future appointments (outgoing calls). For all other administrative work involving other calls, hospital bills, patient billing, drug authorizations and insurance claims, Phone 2 is preferred, but Phone 1 can also be used as and when available. Figure 2 details the patient-service schematic flow in this clinic environment.

Patients come in with or without their companions and wait in the waiting room to be served by the clinic staff. *Greeting and checking-in* patients is a high priority for MA_1, as is attending calls from new patients for appointment and reminding patients regarding their forthcoming appointments. MA_1 is also responsible for making calls to patients regarding their reports, tests, etc. However, if MA_1 is busy with any of the works mentioned above, they are taken over by MA_2 or MA_3, based on their availability, the priority looming from $MA_1 \rightarrow MA_2 \rightarrow MA_3$. *Rooming* the patient (rooming involves preliminary examination on the patient; i.e., blood pressure, weight, etc. are performed in this process and the patient is seated in an examination room for the next available physician) is a priority for MA_2, who also conducts routine checks on drug authorizations and sends out hospital billings. However, if MA_2 is busy with any of the works mentioned above, they are taken over by MA_3 or MA_1, based on their availability, the priority looming from $MA_2 \rightarrow MA_3 \rightarrow MA_1$. The bulk of the administrative work is taken up by MA_3; the work includes insurance verifications and claims, followed by patient billing. While MA_3 assists in any back-log of MA_1 and/or MA_2, any backlog in MA_3 is also complemented by MA_1 or MA_2, based on their availability, the priority looming from $MA_3 \rightarrow MA_1 \rightarrow MA_2$. The patient is checked out by any available medical assistant.

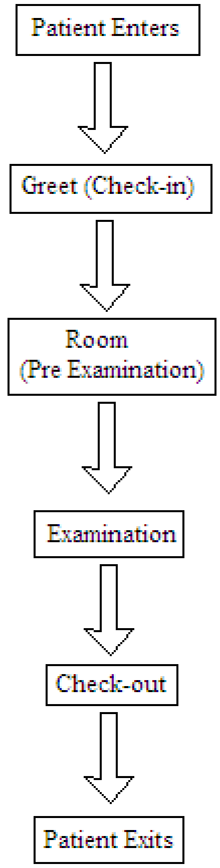

Figure 2. Patient-Service Flow

The physicians distribute their load during the day, with DOC_1 seeing patients in the morning half from 9:00AM through Noon, and DOC_2 seeing patients from 1:00PM through 5:00PM. An effort is made to utilize the exam rooms to their maximum; when a physician is examining a patient in one room, the other room is kept ready for the physician to take over with minimum time slack.

3.2 Building the Simulation Model

Renal Consultants, Inc. provided a detailed list of patient appointment times for a one month period[2]. This list was utilized in creating a distribution for the inter-arrival time of patients.

Based on the data set, we found that roughly 7.5% of the patients were new appointments, as opposed to the remaining 92.5% return appointments. We have made this distinction in our design, since the process time distributions of these two categories, per the physicians and the medical assistants, were different. Table 1 (shown below) details the process time distributions for each of check in, pre-examination (rooming), examination, and check-out, for both first time appointments (new) as well as returning appointments (old). All distributions are in minutes.

[2] Since the patient arrival is 'deterministic' and never falls out of schedule, any issue with irregularity in inter-arrival times do not hold true in this case. Besides, the physicians cannot locate a 'peak time' or a 'normal time' for renal problems. We used a Beta Distribution; small business clinics with similar 'appointment-schedule-dependent' arrival times can use a more parsimonious but equivalent exponential distribution.

Patient-flow Process	Patient Type: New	Patient Type: Old
Check-in	UNIF (0.75, 1.5)	UNIF (0.75, 1.5)
Initial Examination	TRIA (2.5, 3, 4)	TRIA (2.5, 3, 4)
Physician Examination	TRIA (20, 30, 50)	TRIA (10, 15, 20)
Check-out	TRIA (1.5, 2.5, 3.5)	UNIF (1.5, 2.5)

Table 1. Patient-Service Process Times

Other administrative responsibilities of each of the medical assistants, and their process times, per their feedbacks are detailed below (Table 2). The prioritized order of medical assistants for a particular task remains as discussed in the earlier section:

MA1		MA2		MA3	
New Patient Call	TRIA (5, 7.5, 10)	Drug Authorization	TRIA (12, 15, 18)	Insurance Claims	CONST (35)
Other Call	UNIF (14, 16)	Hospital Billing	TRIA (10, 12, 14)	Patient Billing	TRIA (10, 12, 14)
Appointment Reminder	UNIF (3, 5)				

Table 2. Administrative Duty Process Times

Since the simulation is run for an eight-hour day, it is modeled in a way that the clinic completely serves the existing patient (s) in the clinic beyond regular work hours, given that the clinic is closed to entering patients after 5:00PM.

3.3 Clinic Effectiveness: An Utility Measure

Clinic effectiveness (CE) is a utility measure of the medical practice that simultaneously satisfies the *conflicting objectives of patients and physicians* (Swisher and Jacobson 2002). Total utility is derived from a consumer perspective (patient satisfaction) and a clinic perspective (clinic profit). This offers us a more rounded view of utility than we would, were we looking into either one perspective. To provide an intuitive unit of measurement, the CE measure is constructed on a monetary scale, i.e. dollars/clinic day. This section is arranged as follows: sub-subsection 3.3.1 discusses the various constructs of clinic profit, followed by a quantification of patient satisfaction in sub-subsection 3.3.2.

3.3.1 Clinic Profit

Clinic profit is a measure of the revenue coming into the clinic (patient fees) less the clinic expenses (overhead, salaries, rent, etc.). The patient fee was decided at $70/visit for a first-time appointment and $60/visit for all return appointments (HCFA 2009). The appropriate patient fee is added to the CE measure when each patient checks out. Both payroll and non-payroll items drive clinic expenses and were prorated from a 2006 study of regional survey conducted by Resolve Medical Marketing, Inc. (Regional Clinical Office and Staffing costs 2006; prorated). Payroll Expense includes the medical assistant salary, chosen to be $100/day. Non-payroll expenses can be broken down into professional expenses and facility rent. Since the facility of our design is a rented one, we choose a daily rent of $100/day that includes base facility rent of $60/day as well as $20/day for each examination room. The overhead cost of the facility was defined at $30/hour. Professional expenses include office supplies, medical supplies, and liability insurance. This was chosen as $350/day per physician. Table 3 below summarizes the constructs in the clinic profit.

	Construct	$$/day	Rate of Payment
Payroll Expenses	New Patient	$70	per visit
	Returning Patient	$60	per visit
	Assistant Salary	$100	per day
	Assistant Overtime	$20	per hour
Non-Payroll Expenses	Facility Rent	$60	per clinic
	Exam Room Rent	$20	per room
	Professional Expenses	$350	per physician
	Overhead	$30	per hour

Table 3. Clinic Profit Construct

3.3.1 Patient Satisfaction

Wait time is an acceptable quantitative identifier of the qualitative concept of satisfaction. For model implementation, a penalty of $20/hour for patient waiting is used to decrement the CE measure. Prior research (and common sense) suggests that patients are most dissatisfied with unjust or unwarranted waiting times (Mowen et al 1993). Since the perspective of 'justification' varies from one person to another, we once again sought the help of the stakeholders of Renal Consultants, to understand the degree of justified minimum service time as applicable to their clinic. To be selective in penalizing the clinic, the patient waiting time penalty is only imposed for patient visits totaling more than 20 minutes AND in which the ratio of patient waiting time to total patient time is greater than 0.30. Most patients will tolerate a limited amount of waiting time as long as the time spent receiving medical care far outweighs the waiting time. This *service ratio* (Swisher and Jacobson 2002) is used in screening penalty.

4. RESULTS

This section is arranged as follows: subsection 4.1 discusses the statistical integrity of the simulation method and imprecision in the results; subsection 4.2 analyzes marginal utility of the medical resources, both from a standpoint of allocation as well as scheduling; finally subsection 4.3 puts forward an efficient utility frontier for small business clinics with deterministic patient inflow.

4.1 Statistical Integrity and Imprecision of the Result

One run of the simulation equaled an eight-hour work day. This was replicated 130 times to obtain a terminating simulation. Care us taken such that both the system-state variables and the statistical accumulators were cleared at the end of each replication in order that the simulation produced true, statistically independent and identically distributed (IID) replications. Output measures obtained from this simulation are put together in table 4 below:

Output	Average
CE Daily Measure	392.57
MA Salary	300.00
Overhead Penalty	17.2412
Overtime Penalty	34.4823
Patient Fee	1552.40
Patient Wait Time Penalty	8.0990
Professional expenses	700.00
Profit per partner	196.29
Rental expenses	100.00

Table 4. Output from Current Scenario

There are two lines of defense with the choice of '130' replications. One, we wanted the tolerance of our measure to be around 5%. Two, the nature of this medical specialty invokes terminal illness in most patients. Patients who have undergone kidney transplant have an average life span of around 5 years after the transplant, if not less. Patients who have undergone dialysis are also high risk patients. The stakeholder of such a specialty clinic should not rely on data simulated over a long period of time to make business decisions, as the dynamics of the patient base change rapidly. Keeping this in mind, we replicated the simulation for 130 runs, which is roughly equivalent to 6 work-months. The relative precision of 5.1% on the 130 replications is a measure of *tolerance* of our experiment (Kelton et al 2007; Tolerance is a measure of the ratio of the half-width of the CE measure to its mean, the point estimate. The tolerance was found to be 0.051).

4.2 Marginal Utility of Medical Resources

The snapshot from table 5 (next page) clearly suggests that Renal Consultants, Inc. is currently operating at close to full capacity, given the respective responsibilities of the medical resources and the appointment schedule set up by the clinic staff (which, in turn, defines the patient arrival pattern). Naturally, the question for the stakeholders is: Do we have room for improvement? There are essentially two ways to check for performance changes, both accounts for resource utility. The first way is to optimize the allocation of resources by changing the resource count to the maximum threshold the facility can withstand. The second way is to look at the behavioral aspect of the resources (changes in scheduling, prioritization of processes, etc.) with or without changing the resource count. Sub-subsections 4.2.1 and 4.2.2 account for these methods, respectively. A summary view is provided in sub-subsection 4.2.3.

Instantaneous Utilization	Average
MA1	0.8431
MA2	0.8127
MA3	0.8879

Scheduled Utilization	Average
Doc1	0.7985
Doc2	0.9432
ER1	0.4850
ER2	0.4395
Phone 1	0.8358
Phone 2	0.8780

Table 5. Resource Utilization of Current Scenario

4.2.1 Optimization of Resource Count

We ran an optimization in OptQuest by including a new assistant, a new phone, a new physician, and a new examination room based on the scope of the facility layout of Renal Consultants, Inc., and conducted all possible scenarios. The scenario with a new phone turned out to be the optimal one, with a clinic effectiveness measure of $389.47/day. This is lower than the current scenario with a Cost Effectiveness (CE) measure of $392.57/day. In a setting where the availability of resources guides the scheduling of appointments (and hence the arrival of patients), the results are at par with reality. Altering resources in such a system that works at full capacity often tends to shift the balance and hence lower productivity and performance, but seldom heads for the better.

4.2.2 What-if scenarios with Resource Behavior

We model the behavioral change of the resources in two ways. (a) We slack the assumption of the current scenario that all the medical assistants take their break at the same time. Instead, we set up the break schedule of the assistants as a lead function of 15 minutes, such that the physicians' schedules can be changed accordingly. Physicians were earlier tied to the break-time of the assistants. Since we have disallowed the break for all assistants at the same time, one assistant is now always available in the slot previously defined as break. DOC_1 can now serve through an extra hour, knowing that there is at least one assistant to back up. This setting gives a natural boost to patient throughput. The performance measure was recorded at $399.40/day. (b) We slack the assumption of specific responsibilities of medical assistants and assume that each one has the capability to perform all functions, as and when needed. The performance measure was recorded at $388.30. The low value can be explained by the fact that each human resource has a performance curve that gets better with repetition, especially when specificity and complexity are core issues. Mixing of duties probably hindered the repetitious processes in the resources, thereby diminishing the performance curve.

4.2.3 Performance Measure Summary for Renal Consultants

An interaction of the two behavioral aspects of the resource and the effect of increasing the resource count is shown in table 6 below, in decreasing order of utility measure:

Scenario	CE Effectiveness Measure ($$/day)
Changed Schedule	$399.40
Changed Schedule and Resource Count	$395.33
Changed Schedule and Efficiency	$394.20
Changed Schedule, Efficiency, and Count	$392.84
Base case	$392.50
Increased Resource	$389.40
Priority	$388.30
Changed Resource Eficiency and Count	$387.54

Table 6. Performance Measure Scenarios

As evident from table 6 above, changing the schedule of medical resources at Renal Consultants, Inc. seems to give the best 'bang for the buck'. The interaction effect of schedule with count and/or efficiency also seems to give a better measure of CE effectiveness than the base case.

4.3 Efficient Utility Frontier for Small-Business Healthcare Clinics with Deterministic patient arrivals

We define utility (i.e. patient satisfaction) of a small-business healthcare clinic with deterministic patient arrival times, as a function of three variables: the number of resources, the efficiency of the resources and the efficiency of the process.

The 'count' of resources and the postulated increase in the count from an optimized allocation of the resources defines the first variable, denoted as 'resource count' in figure 3 below. Resource count can range from low to high (X-axis).The transition from a 'discrete work responsibility' philosophy to one of 'One for All and All for one' defines the second variable, the elasticity of resource capability, denoted as 'resource efficiency' in figure 3. Resource efficiency is a capability measure that ranges from inelastic to elastic (Z-axis). Finally, the transition from an open-loop system to a closed-loop system defines the third and final variable, the efficiency of the process, denoted as 'resource schedule' in figure 3. A closed-loop system in the service sector has the capability of uninterrupted service, irrespective of the availability of the customer, over the complete period of service time. Resource schedule is a function of process efficiency, and the quality of scheduling renders the process open-loop, or closed-loop (Y-axis).

The bubbles in figure 3 below represent the performance of the clinic (clinic effectiveness) in the 3-dimensional structure. The size of the bubble measures the quality of performance (bigger the bubble, better the performance, hence more $$/day profit).

As seen in figure 3, most of the action is in the Y-axis, and hence we now define the resource schedule as the 'efficient frontier' for marginal utility of medical resources in small-business clinics, given that the patient arrivals are deterministic in nature.

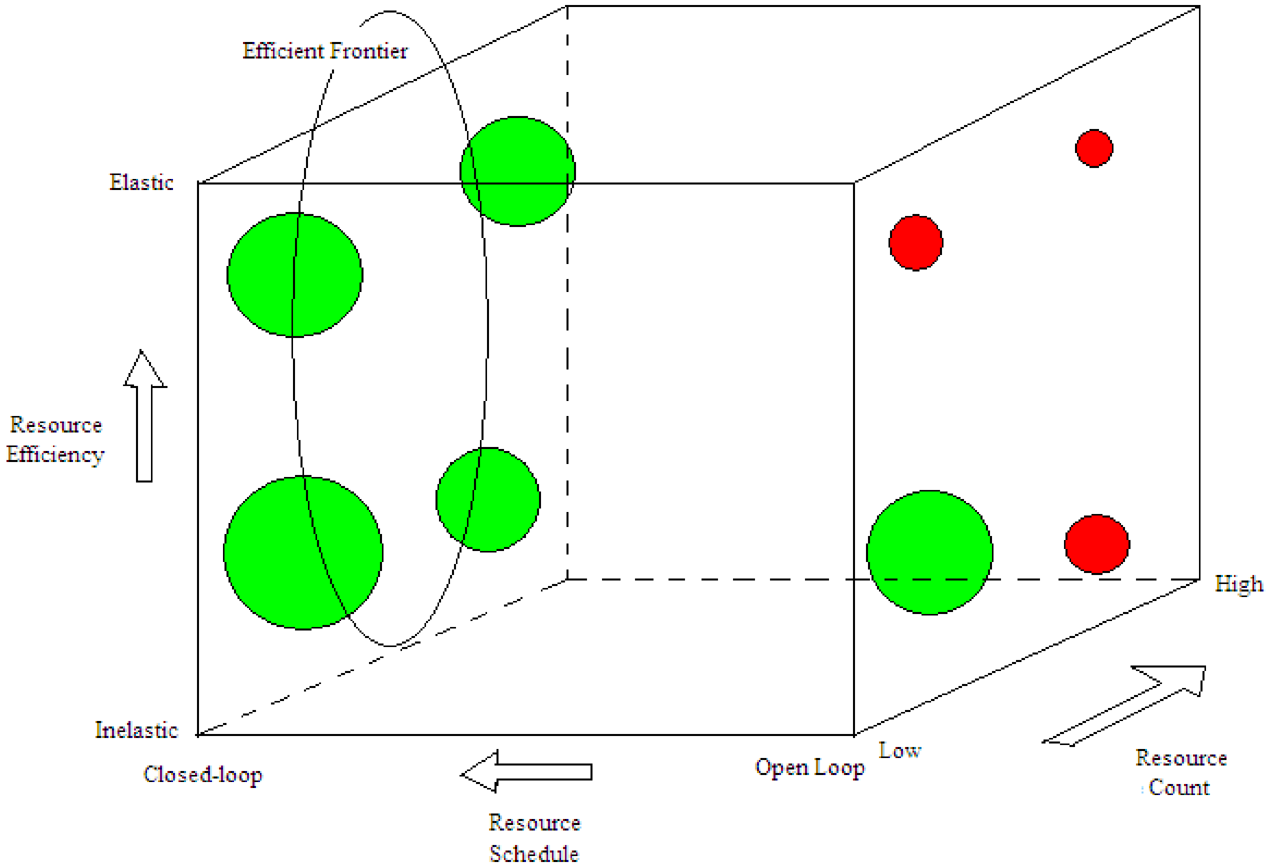

Figure 3. Marginal Utility Analysis of Medical Resources in Clinics with Deterministic Patient Arrival

5. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

A two-physician family practice nephrology clinic has been analyzed using discrete event simulation and system dynamics to shed some light on possible ways of increasing patient throughput and decreasing waiting time of patients, thereby rendering superior performance and profit. We find:

- The mix of resources is constrained by a culture of specificity. Technical resources seem to have better marginal utility than human resources; hence job specificity is an issue. While job specificity lowers multidexterity, specificity in the job also increases efficiency, which in turn increases core competency. Thus, *reduced Multidexterity increases Efficiency, given that Specificity is high.*
- *Resource schedule* is the 'efficient utility frontier' for medical resources in small-business clinics, given that the patient arrivals are deterministic in nature; the marginal utility from this study reinforces the law of diminishing returns in economics, i.e. more is not always merrier.

5.1 Limitations of the Study

The objective of this paper is to reflect upon the operations of a specialized medical clinic. As an initial step, the study surfaces key resource considerations. However, a caveat remains with the use of a single case study to illustrate the point in marginal utility of medical resources with deterministic patient inflow. It would only be in the realm of conjecture to extrapolate from our illustrations and future research might find this study a stepping stone for crafting similar models in the same genre. On a separate note, while the practitioners' perspectives on measurements reflect objectivity, the use of subjective constructs towards objective measurements, while difficult, is abundant[3]. While this paper strives to maintain economies of unit by expressing all factors in the cost effectiveness measure in $/day, patient salaries and satisfaction are not really pieces of the same pie, thereby imposing limitations. Finally, a key feature of a model in speculating beyond idiosyncrasies is its robustness. The 'deterministic' nature of patient arrival could be a limitation; however one might counter argue the richness in process-specificity emanating from this assumption that has the artillery to add novelty to the existing literature.

5.2 Future Courses of Action

Having determined the importance of scheduling, there are several aspects of scheduling in clinic setup that have not been touched in this paper for lack of data. We intend to continue collecting data in collaboration with Renal Consultants to present a better understanding of the marginal utility metric introduced in figure 3. Our future course of work includes, but is not limited to, the following:

- Due to the 'specialty' nature of the medical care, we are unable to slack the deterministic nature of patient arrivals in our future research. However, we intend to probe into some of the patient characteristics that would help the clinic streamline appointment schedules, and hence patient arrivals, to maximize patient flow. As an example, since new patients take more clinic time than returning patients, and since patients with dialysis will take more clinic time than a patient with minor kidney malfunction, this prior knowledge[4] of the 'patient mix', in conjunction with historical knowledge of administrative process times will streamline the scheduling for more efficient patient flow.
- Diabetes has long been correlated to kidney malfunctions. Since the presence or absence of diabetes is indicated in all new patient information, the level of blood sugar can be utilized to forecast the condition of the patient's kidney, which, in turn can forecast the patient's clinic time to compute the position of the patient in the appointment schedule.
- Finally, we want to incorporate the logic of 'companions' with patients in this medical segment[5]. Small-business clinics are typically equipped with not-so-big waiting areas. Under this circumstance, an aging (or dying) patient accompanied by the whole family can pose problems for the next patient in the schedule who might not find a 'seat' in the waiting area. In our future works, we wish to define the consequences of this issue in the patient satisfaction section of our performance measure.

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[3] A case in point is the rich presence of subjectivity on total cost measurements in the purchasing literature. All cost models in purchasing build on the contract pricing between the buyer and seller, and extrapolate based on other intangible cost adders like trust, quality, efficiency, responsiveness, and transaction cost theories (Williamson 1985).

[4] Patient history is a pre-requisite with clinic-driven appointment systems (hence deterministic patient inflow).

[5] Companions attribute to wait-area bottlenecks and patient dissatisfaction due to standing (Swisher and Jacobson 2002).

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