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ASSESSING THE VIABILITY OF AN OPEN ACCESS POLICY IN AN OUTPATIENT CLINIC: A DISCRETE-EVENT AND CONTINUOUS SIMULATION MODELING APPROACH

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ABSTRACT

This paper presents the preliminary results of an ongoing research project investigating the patient appointment scheduling for an outpatient clinic. The outpatient clinic was experiencing three problems of long patient throughput times, a large backlog of appointments, and a high no-show rate. We believe a new scheduling approach called Open Access could address all three problems. To analyze and make recommendations for improvement to patient cycle time we developed a discrete event simulation. To understand the factors leading to a high no-show rate we developed a systems dynamic simulation model. The study identified feasible strategies the clinic management could implement to greatly improve patient throughput time by 50%. Our preliminary results indicate that Open Access is a viable strategy for the clinic. Ongoing work is being conducted to refine the models and determine the best configuration of an Open Access scheduling policy for the outpatient clinic.

1 INTRODUCTION

The management of a dermatology outpatient clinic in Miami, FL were beset by poor performance. The next available appointment was typically twenty weeks in the future due to a large appointment backlog, many patients spent more than two hours in the clinic for a twenty minute appointment, and the clinic had a high no-show rate hovering over 50%. It seems the clinic was in crisis; yet while the management were concerned by the poor performance they were not alarmed. Hospitals operating in other large US cities have similar performance statistics. The outpatient clinic in question is part of Jackson Memorial Hospital (JMH), a major tertiary teaching hospital rated by physicians as one of the nation's top 25 medical centers. JMH is the largest hospital in the Southeastern US, with 1,567 total beds, comprehensive care in 48 areas of clinical services, and occupying 67 acres in the Civic Center area of Miami. So while the clinical staff were concerned about performance they were not alarmed because they felt the poor performance could mostly be attributed to the external influences of the patient community they served.

The outpatient clinic uses a block scheduling policy in which groups or blocks of patients are scheduled to arrive at the same time. The objective of block scheduling like many other patient appointment scheduling policies is to minimize physician idle time (Ho et al. 1999, Soriano 1966). Block appointment scheduling is also useful when the clinic cannot predict whether patients will show-up for their appointments or in other words are a no-show. The outpatient clinic had a high no-show rate of over 50%. The high no-show is not unusual, others have reported similarly high no-show rates (Martin et al. 2003, Moore et al. 2001, Murdock et al. 2002, Tuso et al. 1999). Such a high no-show rate makes managing an outpatient clinic very difficult. In order to deal with the high no-show rate, clinics usually do what Kim and Giachetti (2005) call naïve overbooking. They simply overbook the schedule based on the mean no-show rate. This clinic would typically book 120 patients with expectations of only actually seeing 60 patients. This policy has been shown to be far from optimal, and statistical overbooking can greatly improve the performance (Kim et al. 2005). However, overbooking in healthcare has other ramifications on quality of service and patient satisfaction. In the clinic studied, patient files are kept in a centralized area for the entire hospital. So, not knowing which patients would show up, the clinic has to pull all 120 patient files each day, even though they know less than half of those patients will actually show up. Thus, no-shows contribute to inefficient work in the clinic. Additionally, a no-show occupies a slot in the schedule. Suppose the appointment backlog is 20 weeks. This means that the next available appointment is 20 weeks into the future. Given the 50% no-show rate, if you could identify who was going to show up and not show up then you could reduce the appointment backlog to only 10 weeks. Reducing the backlog would greatly improve what is called access to medical care. Moreover, many patients who cannot wait for their appointment will enter the hospital through the emergency room, a much more costly proposition (DeSalvo et al. 2000).

The scenario described in the outpatient clinic above is not unusual. However, as systems theory teaches us, optimizing a single parameter (physician idle time) in a complex system often leads to an overall suboptimal solution (Ackoff 1999). Optimization of the outpatient clinic is further complicated since there is not necessarily a single stakeholder but several stakeholders in which a pluralistic decision is needed that is satisfactory to all stakeholders (Checkland 1981, Jackson 1991). Moreover, the outpatient clinic is but one clinic in a much larger healthcare system. Operations of the dermatology clinic has impact on other areas within the hospital such as in the emergency department, which we expressed above. If large backlogs in the dermatology clinic as well as other clinics divert patients to the emergency department then the overall costs incurred by the hospital increases.

The conditions described have left many in the healthcare industry frustrated and seeking alternative approaches to scheduling. A new appointment scheduling paradigm called Open Access has emerged that we believe handles the multiple stakeholder concerns and leads to an overall better system design. Open Access is a simple and direct approach to appointment scheduling in which the majority of appointment slots are kept available for same-day appointments. The Open Access concept was developed within the medical profession and the current state of research on the method is entirely based on case studies of mostly successful implementations of Open Access (Murray et al. 2003, Murray et al. 1999, Murray et al. 2000, O'Hare et al. 2004, Ulmer et al. 2002), although a few failures have been reported in the literature (Liddell et al. 2004).

The underlying premise of Open Access is the medical clinic does "today's work today," rather than storing appointments in the schedule and creating a backlog. The chief motivation behind Open Access is to address several flaws in current patient, primarily the long waiting time to receive an appointment and continuity of care. To address these flaws, Open Access proscribes the following policies:

- Practices offer patients same-day access to an appointment regardless of the nature of their problem (routine, preventive, or acute);
- Practices offer the same-day appointment with the patient's primary care physician; and
- Practices attempt to eliminate all waiting within the office.

Open Access is not an open-door policy, patients still receive appointments, but the goal is to give them the appointment on the same day they request the appointment. A normal routine is the patients call early in the day and are offered appointments that day. Some patients might not want an appointment that day, so they are offered an appointment at their convenience. In practice, clinics operating an Open Access scheduling policy offer less than 100% same-day appointments because it makes sense that follow-ups are scheduled.

We had the opportunity to work with the dermatology clinic and investigate whether an Open Access policy would improve the situation. The clinic management wanted to improve the performance of the system but was hesitant about an Open Access policy. They feared they would be inundated with patients if they implemented the Open Access scheduling policy.

In order to meet the research objectives of assessing the viability of Open Access and to improve the clinic performance regardless of the scheduling policy we embarked on a research program strongly influenced by action research. Action research aims to contribute both to the practical concerns of people in an immediate problematic situation and to the goals of social science by joint collaboration within a mutually acceptable ethical framework (Rapoport 1970, p. 499). Action research is also considered an interpretative research method, in which a complex system, such as the outpatient clinic, must be understood as a whole. Action research introduces change to the system and observes the impact of the change. We viewed action research method as appropriate in this situation because the outpatient clinic's main interest is immediate improvement in system performance while the researcher's main interest is in advancing science, in our particular case, understanding of the determinants of Open Access scheduling success.

The paper is organized as follows. First, we describe the research methodology we are utilizing. Then the patient flow process, staffing schedules, and clinic policies are explained. We describe our analysis methodology: how we collected data, modeled the system, and validated the model. Then we present the experiments we conducted to recommend improvement strategies to the clinic. Then we describe the systems dynamic model developed. Our preliminary results with the model are discussed. We discuss the impact of our changes so far and where we think the clinic can go from here.

2 RESEARCH METHODOLOGY

Our research methodology is strongly influenced by Action Research. Action research is an iterative research methodology with the following general phases (Susman et al. 1978).

1. diagnosing – corresponds to identification of the

primary problems.

2. action planning – developing interventions to improve the system.
3. action taking – implementing the interventions.
4. evaluating – determining the impact of the intervention on the system.
5. specifying learning – assessing what was learned.

Action research is mostly used by social scientist with the notable exception of Checkland (1981). Data collection and analysis in action research is characterized by qualitative tools. Here we use quantitative tools and simulation to test the interventions prior to taking action. Consequently, we do not strictly adhere to the methodology but enjoy some of the benefits of interacting with the actual system (Forrester 1994).

To set the stage for our research, we postulate that Open Access will work under the following conditions:

- The demand for appointments is less than or equal to the service capacity.
- The clinic has the capability to influence the demand rate and the service capacity.

The first condition might seem obvious, but many in the medical profession believe demand far exceeds capacity. However, this is not in general true, most clinics have a constant backlog (e.g. 10 weeks) which indicates demand and capacity are in equilibrium. The second condition is necessary because both demand rate and service capacity are variable the clinic must have means to modify both in order to achieve balance. Far greater control can be exerted over service capacity. So service must be as efficient as possible and contingency plans are needed so that service capacity can be adjusted dynamically in order to balance demand.

To make service as efficient as possible we studied the patient flow. We used discrete event simulation to help with this analysis. The second part of the research was to understand the parameters influencing patient appointment scheduling and patient behavior. We used systems dynamics simulation model for this analysis. A description of the data collection, analysis, and simulation models is provided next.

3 THE DERMATOLOGY CLINIC

The project started in May 2004 and continued until May 2005. Data collection occurred throughout the project duration, but the simulation models are based solely on data collected during the months of June and July. We first observed the clinic's operations and developed a flow chart of the patient flow process and a time study chart. Both data collection instruments were reviewed with the clinical staff and revised several times until final versions were obtained. The time study chart was used to record the start time and completion time of each activity. In addition we created a data collection sheet for recording interruptions.

The dermatology clinic operates from 12:30 until 17:00 or the last patient is discharged. Appointments are made in 20 minute increments starting at 12:30 until 15:10. The patient flow, starting when they arrive at the clinic until they are discharged is shown in Figure 1. Patients can check in up to 30 minutes prior to their scheduled appointment. The check-in is performed by a Patient Care Assistant (PCA) and the check-in time was observed to be one minute or less. As patients check-in, they receive a number to be identified throughout the process. We observed that some patients show up later than their appointment time. Patients who arrive after 1530 HRS are not allowed to check-in. They leave the clinic without being treated.

After checking in the patients wait in the waiting area. Meanwhile, the PCA prepares the charts for the checked-in patients and places them on a table. All processes have exceptions to the normal activity flow. At this stage there are several exceptions that we observed. Some patients require permission from their insurance company prior to being served. Some patients lack a patient card that identifies the fees they must pay. These patients are redirected to the financial assessment procedure. Such patients leave the system and are unlikely to return the same day. Exceptions such as these degrade the overall clinic performance and cause many unhappy patients. We discuss this and other exceptions at greater length later.

A nurse retrieves the charts to call in patients for a preliminary assessment. If the patient is a follow-up then they might not require a preliminary assessment. We observed that the nurse only came out to retrieve charts if she had no more charts left.

Once the preliminary assessment is performed, the patient returns to the waiting area, and the nurse places the charts on the disposition table for the doctors. Before calling the next patient for preliminary assessment, she will frequently complete forms included in the chart as well as answer phone calls, answer other nurse's and doctor's questions and similar activities.

At 1:00 p.m. five doctors arrive to the clinic to treat the patients.. The doctors call the patients and take them to the treatment rooms. Although they usually call two patients at a time. they treat only one patient at a time. Doctors give priority to the follow-up patient whom the doctor has treated previously. The doctor's examination time is the same for both first time and follow-up patients.

After the patient is treated, the patient goes back to the waiting area again. Before calling the next patient, a doctor spends some time finishing the paper work for the patient. The doctor places the patient's chart on a rack. Then, a PCA, at the patient's disposition area, picks up the chart from the rack, enters the information into the computer and gives the next appointment date as needed. Finally, she places this chart on the table at the disposition area separated from the charts for the doctors. There are two PCAs performing this process.

A nurse picks up these charts and calls the patient from the waiting area to be discharged. Before calling the next patient, the nurse must complete a form with additional patient information and get a copy of the doctor's examination analysis. If the patient is coming back for a particular exam, the nurse will provide to the patient the indications of the procedures required for the exam.

There are currently two nurses performing the preliminary assessment and discharging:

1. Nurse1 starts at 12:30 hours by performing preliminary assessment. Once preliminary assessment is done for all patients in the clinic at the moment, she turns to discharging the patients if any available.
2. Nurse2 starts at 13:00 hours with preliminary assessments until there are patients to discharge. Then she starts to discharge the patients till the end of the day.
3. Both Nurses perform both preliminary assessment and discharging on a First Come First Served basis.

We observed that the processing of patients is not a strictly first-in first-out (FIFO) process. Once a patient is checked in the processing is done based on the ordering of the patient charts. If the charts get shuffled out of order then the FIFO processing is upset. Moreover, physicians will skip over patients if the patient is a follow-up to another physician. This is done for clinical reasons called continuity of care. We also observed that coordination of activities is informal. Staff are not assigned to particular tasks but float between tasks presumably with the objective of addressing bottlenecks. The first appointment is at 12:30 and patients are encouraged to arrive up to 30 minutes prior to their scheduled appointment. Yet, the PCA and nursing staff do not arrive until 12:30 and the physicians do not arrive until 1:00. So a patient who arrives early, by recommendation of the clinic will wait almost a full hour before being seen by the physician.

The system has many exceptions, where an exception is defined as a deviation from the standard flow described above. The reason for many exceptions is due to patient specific issues; each process deviation is to handle a special case encountered in the patient population.

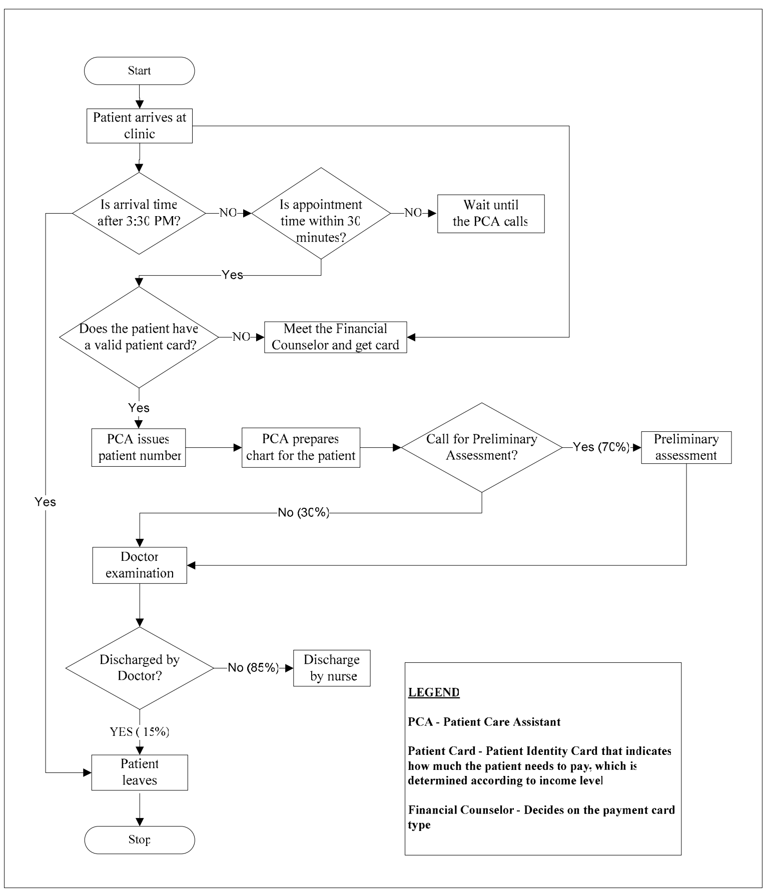

Figure 1: Flowchart of Patient Process

Table 1: Summary of Data Collected

Activity	Sample Size	Mean (minutes)	Standard Deviation (S.D)	Minimum (minutes)	Maximum (minutes)	Mean to S.D ratio in %
Wait for Preliminary Assessment	368	38.8	26.1	0	95	68
Preliminary Assessment	**283**	**2.3**	**1.5**	**1**	**10**	**63**
Wait for Doctor Examination	274	24.6	14.9	1	69	61
Doctor Examination	**417**	**21.1**	**12.6**	**3**	**78**	**60**
Wait For Discharge	305	30.8	16.5	4	88	53
Discharge	**285**	**2.6**	**2.5**	**0**	**18**	**98**
Discharge Chart Processing	40	4.0	1.5	1	8	39
Throughput Time	595	110.1	32.2	52	203	29

4 PROBLEM ANALYSIS METHODOLOGY

The data collected is summarized in Table 1. The value-added activities are in bold-faced type. Note, check-in was not included because it was observed to take less than a minute on averaged and was deemed not critical to analyzing patient throughput time.

4.1 Discussion on Patient Throughput Time & Cycle Time

The average patient throughput time is 110 minutes with a standard deviation of 32 minutes. Approximately 75% of this total time the patient is waiting. If we calculate a theoretical throughput time in which the patient experiences no waiting; then the minimum possible (although likely never to be achieved) throughput time is 2.3 + 21.1 + 2.6 = 25.6 minutes. Consequently, there is significant room for improvement.

Cycle time is the rate at which patients exit the clinic. The cycle time is dictated by the bottleneck activity. The longest activity is the doctor examination at 21.1 minutes. With 5 doctors then on average a patient is processed every 4.2 minutes (21.1 minutes / 5 doctors). The actual cycle time observed was 5.6 minutes.

The usefulness of the theoretical throughput time and cycle time is to assess how well the clinic is performing. For the dermatology clinic the actual cycle time (5.6 minutes) is very close to the theoretical cycle (4.2 minutes) but the actual throughput time (110 minutes) is much longer than the theoretical minimum throughput time (25.6 minutes). The reason for this is the clinic is currently running under a batch process scenario. Figure 2 shows that almost 75% of the total patients seen in a day arrive in the first hour. It must be noted that the last arrival is scheduled for 2:20 PM as the last appointment for which the patients arrived during the study period was 2:50 PM. The scheduling policy in use is a batch or block scheduling process. As a result high waiting times result since a backlog of patients is built up in the waiting room even before the doctors arrive. If the clinic instead moved towards a more balanced or individual processing scenario then it should be possible to greatly reduce the throughput time without an increase in resources.

For preliminary assessment and the doctor examination the waiting time is much higher than the time taken to provide the corresponding service. The high waiting time for preliminary assessment and doctor examination can be attributed to the delayed starting of the doctors and nurses. Although, the nurses start preliminary assessment at 12:30 PM (the first appointment time), the patients belonging to the appointment time checked in 30 minutes earlier. The doctors start at 1 PM which is 30 minutes after the first appointment time. Since preliminary assessment is relatively short there is no reason to have patients arriving up to one hour prior to the arrival of the doctors.

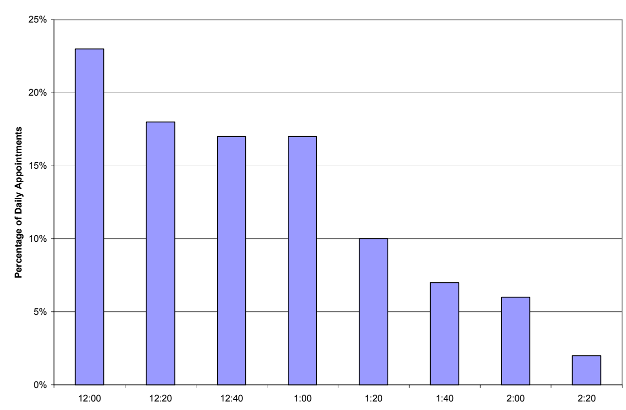

Figure 2. Patient Arrival Distribution

In addition to the process service times and waiting times we observed the process and collected data on staff interruptions. Staff interruptions included answering telephone calls, answering patient inquiries, requesting translation services, and so forth. Interruptions greatly reduces the availability of staff for the main activities described in Table 1. Examining the discharge patient activity we see it was 2.6 minutes on average. Yet the waiting time for discharge is 30.8 minutes. Part of the reason for the high waiting time is due to the way staff is assigned and also due to the interruptions. Discharging patients was a main bottleneck in the process that can be easily remedied.

Other observations were that the clinical staff spent considerable amount of time completing paperwork. We are aware of many healthcare facilities that are investigating innovative uses of IT to reduce the documentation burden. In this case, changes to the charting procedures and technology were out of scope since it was a hospital-wide system that the clinic must use.

4.2 Preliminary Recommendations

Based on the observations and quantitative data analysis, we made the following recommendations to the clinic management in order to reduce the patient throughput time.

- Discharging – The activity of discharging the patients should be done immediately after the doctor examination is over instead of making the patient wait until his / her history chart information is entered into the computer. The average waiting time for discharging is 30 minutes. Hence by discharging the patients ahead of chart processing, the throughput time will be reduced by 30 minutes.
- Patient Appointment Scheduling – The patients must be scheduled to arrive at the clinic such that they don't need to wait until they receive service. If the patient arrival rate matched the service rate then the clinic could have a flow system. The obstacle to this approach is the high no-show rate (over 50%). Instead we recommended that patient arrivals be more evenly scheduled throughout the day. The recommended schedule was that five patients arrive every 30 minutes.
- The service providers (doctors and nurses) should start working at the same time as the first patient appointment (12:30 HRS). Currently the doctors arrive about 30 minutes after the first appointment time. This results in the patients waiting unnecessarily until the doctors arrive.
- Order in which patients are called. The patients must be called for service (preliminary assessment, doctor examination) in the order of their patient number. If the patients are called out of order, some patients (especially the ones arriving during the first one hour) have a much higher waiting time and consequently longer through put time and large difference in maximum and minimum waiting times. In addition, this causes the other patients to interrupt the normal service to ask why they were not called. By calling the patients in order, the waiting time for service will be less scattered around the average time and the high variation is minimized.

5 SIMULATION MODEL TO ANALYZE RECOMMENDATIONS

The data collection and analysis were sufficient to identify bottlenecks and other process anomalies that limited system performance but in order to optimize the process and assess the impact of design changes we created a discrete event simulation model. Here we provide an overview of how the simulation model was constructed.

The model was built using the ARENA software. A snapshot of the animation is shown in Figure 3. ExpertFit distribution fitting software and ARENA's Input Analyzer were used to develop probability distributions for the patient arrival rate and service rates. The process flow of the model was verified using the trace function in ARENA.

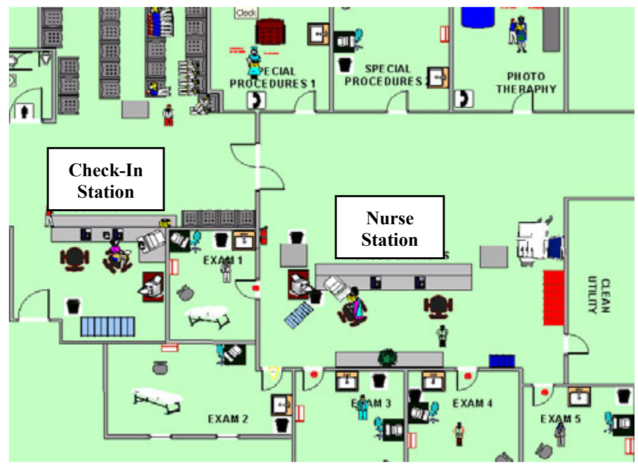

Figure 3: Animation Snapshot.

We conducted several experiments. The optimal design we found was to have doctors do a greater share of the discharging (doctors discharge 50% of the patients), to rearrange the scheduling blocks and evenly distribute them throughout the day, and more formal definition of the roles of PCA's and Nurses to better balance the demands on preliminary assessments and discharging. The simulation model predicts these changes can reduce throughput time to 66 minutes on average. If an additional nurse was hired then patient throughput is predicted to be 58 minutes on average. Consequently, the simulation model indicates a 50% reduction in throughput time is possible.

5.1 Intervention

The data collection, quantitative data analysis, simulation modeling and experimentation represent phases 1 and 2 of the action research program. The next phase is to make take action in the system so that the changes can be evaluated. We met with the clinic management in October 2004. The results of our analysis and the simulation management were presented. We discussed interventions that could be done in the short-term. The intervention consisted of starting nurses and physicians earlier and modifying the assignment of tasks of nurses and PCAs. The impact of these changes can then be evaluated and further interventions planned.

6 SCHEDULING SYSTEM AND POLICIES

The discrete-event simulation model was done as a prerequisite to make patient flow as efficient as possible in preparation for Open Access scheduling. The next part of the research was to understand the relationships between the scheduling system, patient demand, and service capacity. To represent these relationships we constructed the stock and flow diagram shown in Figure 4. The diagram is for the current scheduling system.

System dynamic simulation models, also called Stock and Flow models, use differential equations to model the dynamics of continuously changing variables (Sterman 2000). The primary benefit of this modeling approach is to capture the feedback loops that are important to most all complex systems. Our hypothesis is that the scheduling system influences patient demand behavior and other external parameters which will in turn change the performance of the outpatient clinic. Existing studies of scheduling systems for healthcare do not consider how the system influences patient behavior, which can greatly impact the efficacy of the scheduling system. For example, the further in the future the next available appointment, the higher the no-show rate is (Murdock et al. 2002).

The systems dynamic model has three types of variables: stocks that represent accumulations, rates that represent the flow into and out of stocks, and auxiliary variables that represent other parameters impacting system behavior. To explain the simulation model we will describe the input/output relationships for each stock.

In the diagram there are three stocks (appointment requests, appointment booked, and appointments realized). The first stock represents the accumulation of appointment requests. Patients are disaggregated into first time patients and follow-up patients who make appointment requests. The appointment request stock represents all the calls patients would make. A booking rate turns those requests into appointments (the appointment booked stock). A small fraction of patients will balk at this point depending on the waiting time. The appointment booking time is reduced by the number of patients scheduled which is the overbook rate plus the scheduled rate. The appointments realized stock is the actual patients being served at a particular time. This stock is emptied by the actual service rate of the clinic and the no-show rate.

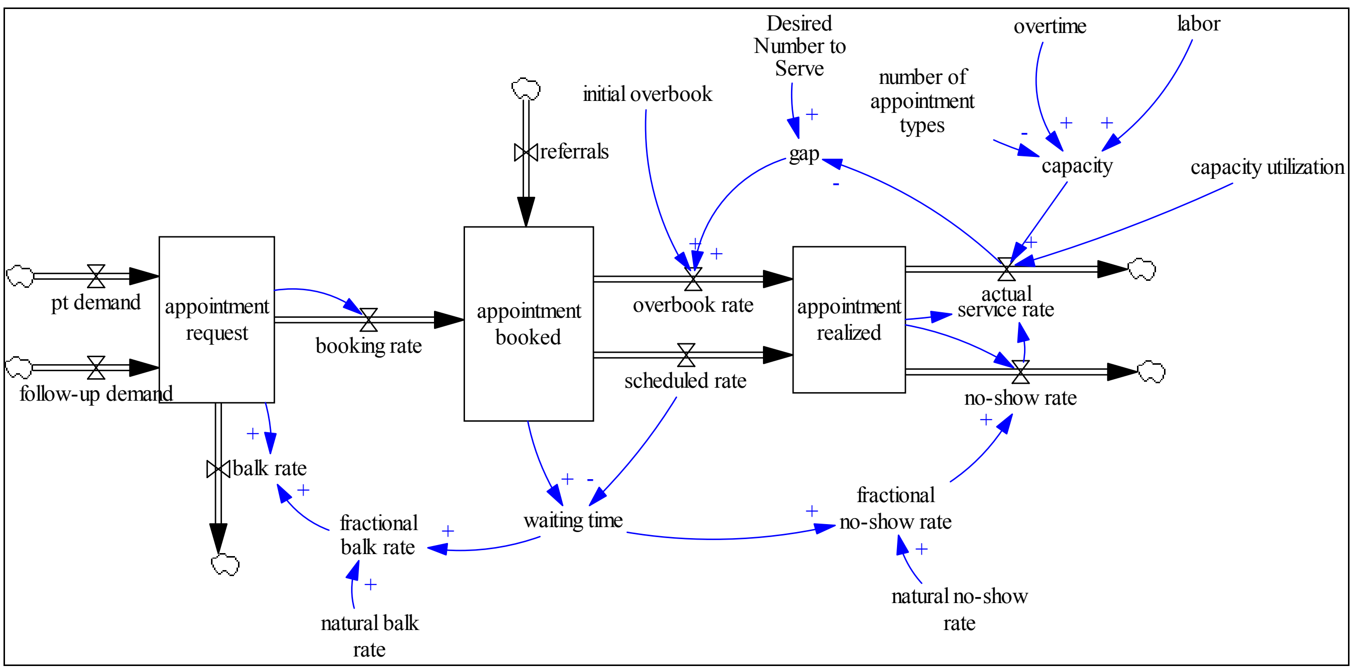

Figure 4. Initial Stock and Flow Model for Outpatient Clinic Operations

Important feedbacks in the system are described next. If the backlog grows too large patients start to react, predictably, by not showing up for the appointments. This is essentially balking behavior, in this case there is no physical queue of patients but a virtual queue as represented by the appointment book. In the clinic being studied the backlog of appointments sometimes grew very large. We hypothesized there was a correlation between appointment backlog and no-show rate. Using the scheduling system we would note the next available appointment and then go forward to record what the no-show rate was. For example, in the last week of August the backlog was 23 weeks we would then count 23 weeks following that date (i.e. the second week of February) and recorded the no-show rate of 55%. The scheduling system only archives one year of data so we were only able to collect 9 data points so far. The results of our correlation analysis are shown in Figure 5. The r^2 value is 0.26 indicating a very weak correlation; however 9 data points are insufficient and we are continuing data collection to see if with more data a stronger correlation emerges. We are also investigating more sophisticated models that include other factors (Garuda et al. 1998) that have been shown to be predictors of no-show behavior.

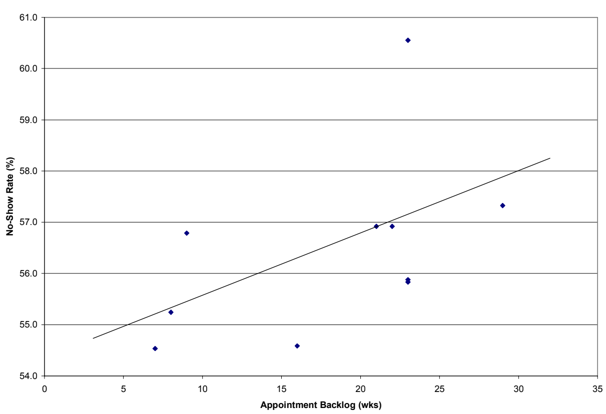

Figure 5: Relationship between No-Show Rate and Appointment Backlog

We have collected data for all the variables in the model except for the natural balk rate and the natural no-show rate. These values can be calculated from the observed values of fractional balk rate and fraction no-show rate respectively. Appointments in the clinic come from internal sources (e.g. reference from emergency department) and from patients. The clinic maintains no data on the demand for appointments. We collected data for a one week period that showed a mean demand for 60 appointments per day. This is confirmed by the clinical staff as reasonable. The clinic serves on average 67 patients. So, in fact the mean service capacity is greater than the mean demand rate. The problem is the variability, on some days it is possible the demand will exceed service capacity. The clinic would need contingency plans in order to deal with these days.

Thomsen et al. (1999) present a trajectory for validating simulation models of complex organizational structures such as we find in the outpatient clinic. We are in their second stage called Intellectual Experiments based on reasoning. With more data to confirm some of the relationships we will be better able to test the validity of the model.

As an example of our preliminary results we shown in Figure 6 the appointment backlog stock when the rate variables are set to the values observed in the clinic. The initial condition were zero backlog. As expected the backlog continued to increase largely due to the variability in the demand and service rates and then it levels off as the feedback loops start to compensate for the inequilibrium.

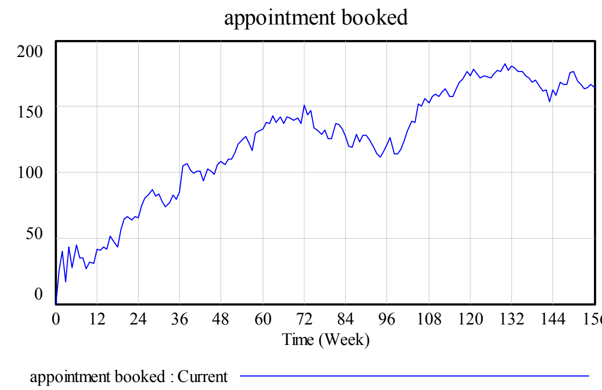

Figure 6: Appointment Backlog

7 CONCLUSIONS

We set out to understand the conditions under which Open Access would work. In the process of conducting our research we worked to improve the performance of the clinics operations. The data analysis suggested several reasonable policy changes that management could implement in order to make improvements. The clinical management instituted two of those improvements, the starting of nurses and physicians at an earlier time and the assignment of staff to tasks. However, while the study was ongoing the hospital was experiencing financial problems and had layoffs. Staff morale was predictably low and we believe this influenced the implementation of the changes. We observed that they slowly reverted to the old way of doing things. We hope to work with them to identify a strategy to institute the changes permanently.

Changes to the patient schedule are more difficult to implement in the clinic because the clinic does not have absolute control over the appointment booking process and the legacy scheduling system is inflexible not accommodating significant changes in scheduling policy. For example, other clinics in the hospital are able to book appointments in the dermatology clinic. This may for the time being prohibit attempts at Open Access. Some of the community clinics operated by the hospital do not have this restriction and they are more aggressively pursuing Open Access.

Open Access is a new concept of how to design and operate a scheduling system for a healthcare provider. Open Access was initiated by practitioners. To date implementation and operation of Open Access has been accomplished by trial and error. The preliminary attempt at simulation modeling of Open Access in this proposal is likely the first such attempt. While the systems dynamic model is still being validated, it provides a useful tool to discuss the relationships between important factors in the system. This discussion promotes learning of the system which we hope will help generate ideas for best operating the system and also overcome resistance to change among the clinical staff.

We continue with the research program; we intend to collect more data, refine our models, and evaluate the impact of any changes to the system performance. The work contributes to a better understanding of Open Access and scheduling policies in outpatient clinics. Moreover, the action research approach is little utilized by researchers steeped in operations research. A benefit of the action research approach is it involves researchers as participants in actual systems problems. We feel that action research can be adapted (as we did) to incorporate operations research tools while maintaining its interpretative research focus.

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