A Hybrid Modeling and Simulation Methodology for Formulating Overbooking Policies

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A Hybrid Modeling and Simulation Methodology for Formulating Overbooking Policies

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Abstract

System dynamics modeling and discrete-event simulation have been applied in the health care industry in system improvement initiatives. Although each has its strengths and weaknesses, few studies have demonstrated how these two approaches could be brought together to improve the quality of health delivery. In this paper, a feedback-based hybrid modeling and simulation methodology has been developed, one that uses a system dynamics model for policy making and a discrete-event model for day-to-day clinic operations. This method is applied to support the formulation of overbooking policies in an Orthopedic clinic to achieve the strategic goal of a maximum appointment delay of 30 days. First, the system dynamics model is run to identify the best overall overbooking policy, which is then fed into the discrete-even model to evaluate its impact on day-to-day operations in terms of the patients' time in system. In this way, the policies developed by this hybrid modeling and simulation method address both the strategic (long-term) as well operational (short-term) goals of a clinic. Additionally, the approach also demonstrates that though overbooking is a commonly practiced to mitigate the negative effects of no-shows, it also can be an effective intervention strategy to reduce appointment delays.

Keywords
Overbooking, Appointment Schedule, Discrete-Event Simulation, System dynamics modeling

1. Introduction

Studies have shown that the U.S. health care delivery system is poorly prepared to meet the growing demands of its population [1]. Access to health services is increasingly difficult as evidenced by long wait time, also known as appointment delay. In addition, high rates of patients' no-shows result in significant waste of already rare resources in clinics [2]. Both of these issues however, are not unrelated. Indeed, researchers have found that a somewhat linear relationship does exist between appointment delay and no-shows [3]. Therefore, effective intervention strategies aimed at decreasing appointment delays will also decrease no-shows, thereby enhancing health care delivery. As such, appointment delay may be regarded as a performance measure to assess the quality of health care delivery systems.

In Veterans Administration Medical Centers (VAMCs), appointment delay is a critical performance measure. A closely related and probably more recognizable measure within VAMC's is the percentage of patients seen within 30 days of their appointment requests. However, interviews and data analysis performed during the course of this project has revealed that this threshold is rarely met for most patients. Indeed, delays of 3 months or more are not uncommon. The primary reasons cited is insufficient capacity (i.e. providers and nurses) given the volume of both new and established patients. However, time studies performed at the site in some of the specialty clinics have shown that while clinic capacity is defined in terms fixed appointment slots size (e.g. 40 minutes for new patients in Orthopedics), most providers rarely use more than half the time of those slots with patients.

In this paper, the practice of overbooking has been studied in light of the apparent availability of additional capacity. Specifically, the objective is to quantify the potential impact of an overbooking policy, not only from a strategic and long term point of view, but also from an operational and short term one. Indeed, while it is expected that some overall overbooking rates may allow the clinic to achieve the aforementioned appointment delay goal, those same rates may potentially, when the right conditions are present, threaten operational performance, particularly in terms of patients' total time in system. The total time in the system of a patient may increase dramatically, thereby resulting in patients' dissatisfaction. It results therefore that overbooking rates that are promising from a strategic standpoint may not necessarily be appropriate for clinic day-to-day operations. Therefore, it is necessary to consider overbooking policies formulating both strategically and operationally. This paper has discussed the hybrid modeling and simulation methodology – composed of a systems dynamics model on one hand, and a discrete-event model on the other – which was developed to help formulate overbooking policies. An Orthopedic specialty clinic has been used as an example to demonstrate this methodology.

First, a review of the literature is presented. Section 3 then describes the methodology. In section 4, the hybrid methodology is applied in a real world example, an Orthopedics specialty clinic in a VAMC, to illustrate how a practical overbooking policy may be formulated.

2. Literature Review

The application of systems engineering tools to improve health care delivery system has been advocated, particularly in the joint report from the National Academy of Engineering (NAE) and Institute of Medicine (IOM) [4]. Systems engineering focuses on the design, control and orchestration of system activities to meet performance objectives [5]. System modeling and simulation methodologies in particular have been successfully in a wide variety of applications, both in and outside of the healthcare field.

Indeed, system dynamics modeling has been recognized as an appropriate method for improving healthcare management, and therefore used in various healthcare settings to explore strategies or policies [6]. Moreover, researchers argue that the strategic perspective offered by the system dynamics approach and its emphasis on the interactions between processes facilities the study of health care systems [7]. On the other than, discrete-event simulation has proven particularly useful as an analysis and improvement tool to assist operational decision makings in healthcare settings as they are often plagued by complexities and uncertainties [8]. Discrete-event simulation, system operations can be represented by a set of states, with transitions among states occurring when certain events take place, often in a probabilistic manner [9].

Research abounds on the applications of both modeling and simulation paradigms in healthcare. However, little has been published in regards to harnessing the benefits that a hybrid modeling approach could provide to resolve issues in a complex environment. One of the exceptions however, is Rohleder et al. who used discrete-event simulation to support new facility design and then a system dynamics model to help predict implementation problems of new design [10]. Nevertheless, while they applied both types of simulation to the same problem, a feedback of information between these two worlds was never discussed.

3. Methodology

This study was conducted in an Orthopedic clinic that provided health care services for three types of patients: new patients, regular established patients and ambulatory surgery patients. After their first visits, new patients might be sent to either ambulatory surgery or back to the regular clinic for established follow-ups. Upon completion of ambulatory surgeries, patients were sent back to the regular clinic for subsequent follow-ups. Since ambulatory surgery patients were operated in an operating area that is separated from the Orthopedic clinic, we only focused on the regular clinic services for new patients and established patients in this study. Nevertheless, the provider's absence from the clinic when performing surgery was accounted for in the resource availability component of the models.

In this study, each overbooking policy was evaluated from two perspectives. From a strategic standpoint, they were evaluated with respect to their ability to achieve the strategic goal of reducing appointment delays to maximum of 30 days. From an operational standpoint, they were evaluated with respect to the time patients would be expected to spend within the clinic on any particular day. This latter evaluation was performed by first assessing the feasibility of the allocation of the overbooking capacity to the different types of patients. The system dynamics model focused on the strategic factors that impacted the overbooking policy and the relationships between them. The discrete-event model focused on the clinic operational processes. Through the system dynamics model, an overall overbooking rate that made the model achieve the strategic goal (maximum 30 days of appointment delay) was obtained; as well as such overbooking capacity was allocated between different types of patients. Then, this overbooking rate and allocation policies were implemented in the discrete-event model to investigate the expected operational performance of the clinic. The operational performance measurement being used in this study was the patients' total time in system. A total time in system that did not exceed 30 minutes plus the time spent with the provider was set as a performance goal.

3.1 System Dynamics model

First, a system dynamics model was used to study the impact of various overall overbooking rates on appointment delay. The system dynamics model distinguished two types of patients, new patients and established patients by building a scheduling system for each type of patients. A meta-model represented the generic scheduling process, as shown in Figure 1. The input rate of patient's backlog was generated by the number of appointment requests per month; while the output rate was regulated by the number of requests getting scheduled per month. Given the strategic goal of appointment delay, the monthly demand of patients was determined by the total number of patients in backlog divided by the maximum appointment delay. Then the available capacities were determined by both monthly demands of patients and overbooking rate. This logic was developed for both new patients and established patients and integrated into a single model where clinic capacities were shared. The result of this logic was an essentially balancing loop that constantly sought to bring the system to the desired strategic goal.

The capacities were distributed between new patients and established patients based on their monthly demand. For instance, if the demand of established patients in one month was four times as much as new patients, system dynamics model would distribute one fifth of capacities to new patients, and the rest to established patients. For this model, capacity allocation was only determined by the ratio of monthly demands of established patients over those of new patients, and would adjust dynamically with varying monthly demands to achieve the long term strategic goal. In this way, the capacity allocation policies might change within a certain range. However, some margin values within those ranges may cause clinic to miss their time in system performance goal. For example, if the system distributed too many overbooked capacities to established patients, increasing number of established patients would be scheduled at the same time. Then with the number of arrival patients increasing dramatically, both established patients and new patients would have long in-clinic waiting time for their appointments. In order to investigate these potential risks, a discrete-event model was built and used to evaluate the overbooking policy proposed by the systems dynamics model.

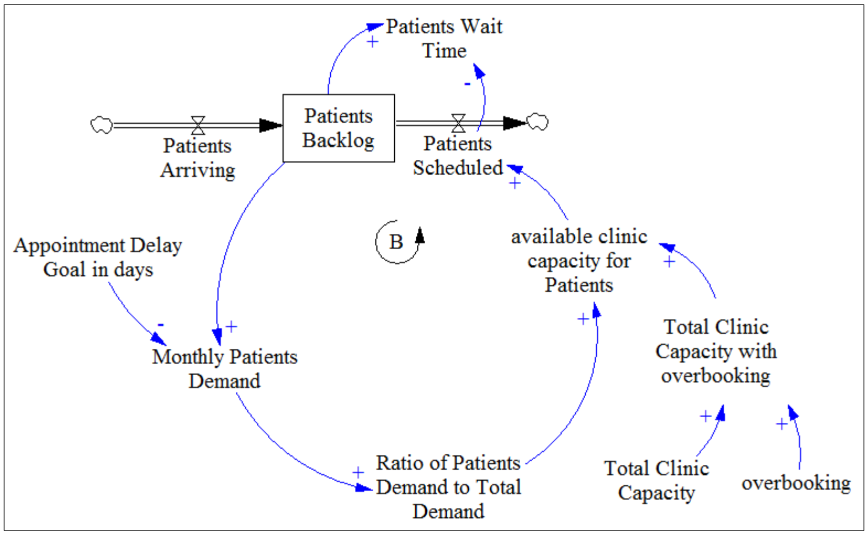

Figure 1: Meta-Model of Scheduling System

3.2 Discrete-Event Model

In Orthopedic clinic, there were three providers, two nurses and three exam rooms. Furthermore, new patients had 40 minutes appointment time slot and established patients have 20 minutes appointments time slot. The discrete model was developed in Flexsim Healthcare®, and used data from internal reports and from a time study that was performed by the research team. The patient flow was shown in Figure 2, and patient track implemented in Flexsim Healthcare was shown in Figure 3.

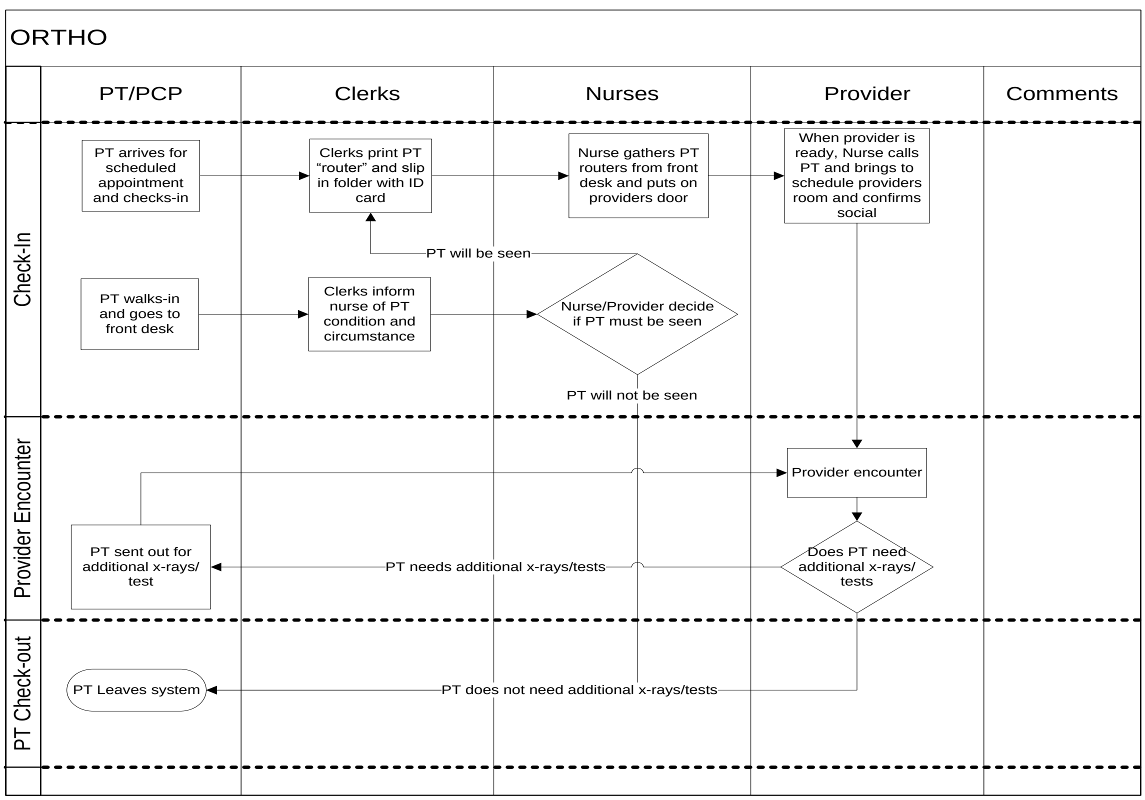

Figure 2: Patient Flow of Orthopedic Clinic

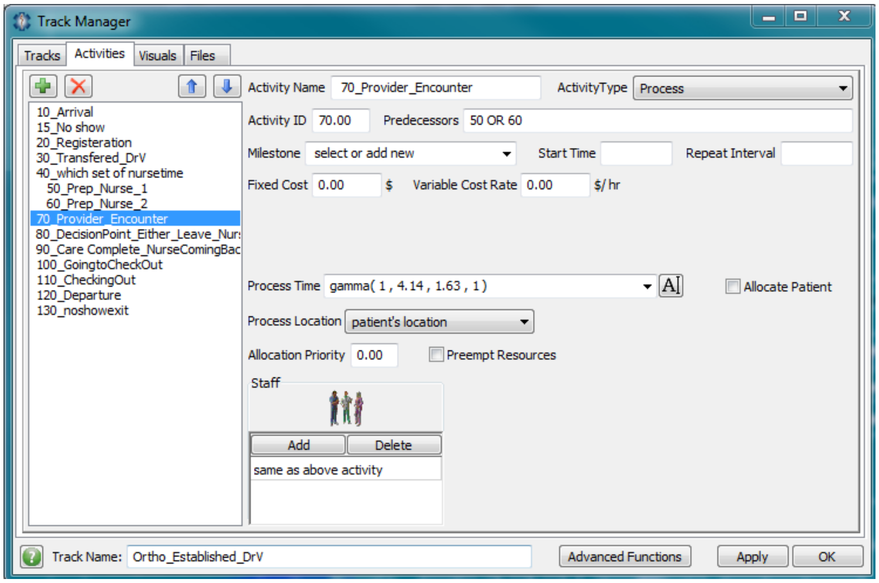

Figure 3: Flexsim Healthcare Patient Track for Orthopedic Established Patient

The model generated patients based on hourly arrival rates obtained from scheduling records. The process times (i.e. check-in, nurse screening, consulting, and check-out) used by the model were the distributions fitted with data from the time study. Data analysis showed that the average no-show rate of Orthopedics is 7.4% for established patients and there was no significant difference between providers in terms of their process time. It was assumed however that new patients would show up for their appointment. Overbooking was implemented by increasing the hourly arrival rates of two types of patients, according to the capacity allocation ratio provided by system dynamics model. For instance, if the overall overbooking rate was 50% of initial clinic capacities and system dynamics model distributed one fourth of capacities to new patients and the rest to established patients, the number of new patients generated would be increased by 10% of initial number in base model, and 40% for established patients.

3.3 A Hybrid Modeling and Simulation Methodology

The mechanism of this hybrid methodology was to involve operational constraints or feedbacks from the discrete-event simulation back to the system dynamics model to enhance strategic decision-making capability. This was captured conceptually in Figure 4. The policies proposed by the system dynamics model, including overall overbooking rate and corresponding capacity allocations, were implemented in the discrete-event model to investigate their operational merits. If patients' time in system was unacceptable of one certain policy, then a constraint would be send back to system dynamics model so that a better policy could be found. Conceptually, this feedback loop would be travelled until a satisfactory policy from both a strategic and operational perspective was found.

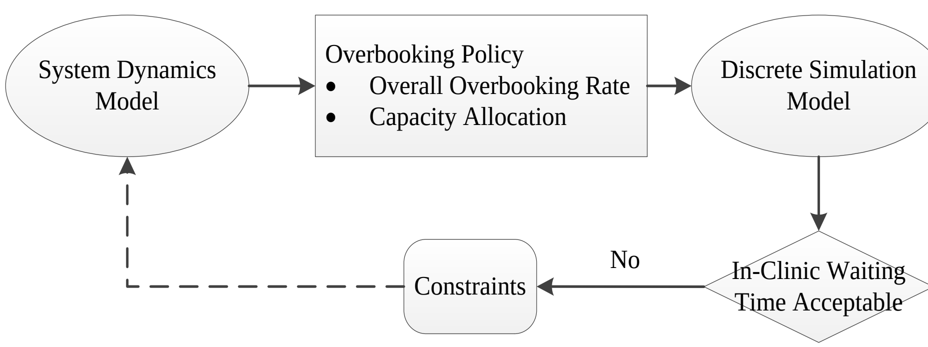

Figure 4: Mechanism of Hybrid Modeling and Simulation Method

4. Results

Based on our time study, we found that the average consulting time that the providers spend with patient was about 21minutes for new patients and 11minutes for established patients, which were both much smaller than the slot size, 40 minutes for new patients and 20 minutes for established patients. Thus, it was reasonable, at least in theory to investigate high overbooking rates, even up to 100%. Therefore, several simulation experiments were performed, in which the overbooking rate varied from 10% to 100% in increment of 10%. In addition, an additional scenario was investigated in which the overbooking rate was chosen to match the average no show rate of 7.4%. This was a common practice in veterans' medical centers, as it mitigated the negative effect of no shows on the utilization of resources. Furthermore, as stated earlier, a strategic appointment delay goal of 30 days was adopted.

The outcome of these experiments was summarized in the boxplot shown in Figure 5. It was evident that the common approach to overbooking by the average no-show rates did not result in significant improvement in appointment delay performance. In other hand, this practice was largely ineffective with respect to patients' experience. The results also indicated that in this clinic, overbooking rates of 80% or higher were necessary to achieve the appointment delay goal of 30 days. In fact, with a 90% overbooking rate, 75% of the patients in the Orthopedic clinic would be seen by their providers within 30 days of their appointment request date. In addition one could observe that the variability in appointment delay decreased dramatically as the overbooking rate increased. Therefore, in theory, overbooking could be a very powerful strategy toward maintaining consistency in the performance of the clinic.

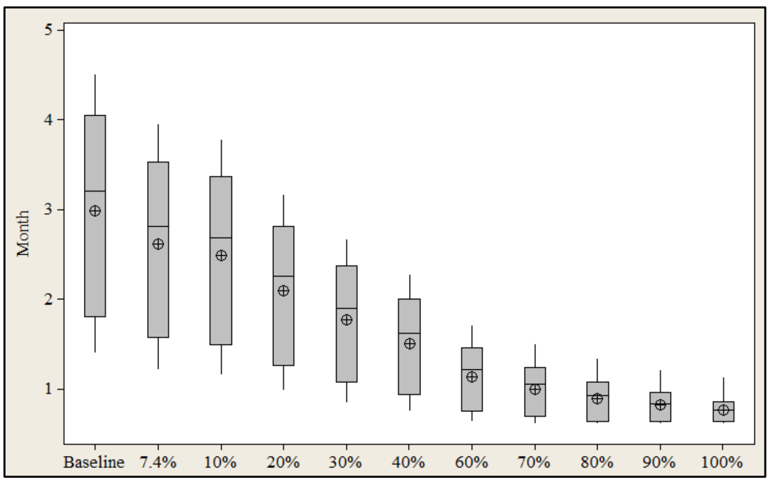

Figure 5: Appointment Delay of Different Overbooking Rates

However, what remained to be established was whether such high overbooking rates could be implemented in day to day operations. The discrete-event simulation model discussed in section 3.2 was used for that purpose, considering an overbooking rate of 90%. The allocation of this overbooking rate between new and established was determined. This was achieved by first using the systems dynamics model outputs in order to calculate the ratios of monthly demands of established patients by monthly demands of new patients were generated by system dynamics model. As shown in Figure 6, these ratios ranged from 3 to 26, with an average of 10. As the distribution of the overbooking capacity between new and established patients' changed constantly over time in the system dynamics model, five allocation points were identified and retained for the discrete-event model: the minimum, first quartile, median, third quartile, and maximum. This information was summarized in Table 1.

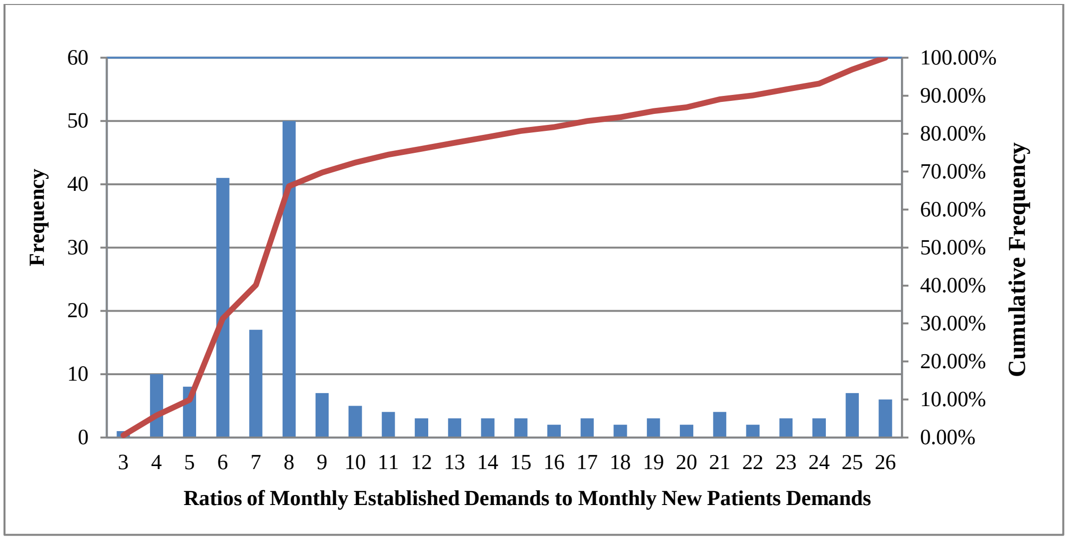

Figure 6: Frequencies of Ratios of Monthly Established Demands to Monthly New Patients Demands

Table 1: Overbooked Capacity Allocation

	Ratio of Established over New	New Patients	Established Patients	Total
Minimum	3	22.5%	67.5%	90%
1st Quartile	6	13%	77%	90%
Mean	10	9%	81%	90%
3rd Quartile	12	7%	83%	90%
Maximum	26	4%	86%	90%

The overbooking rates above were implemented by increasing hourly arrival rates of new patients and established patients respectively in discrete-event model. We assumed that overbooking was distributed evenly per hour, since it was assumed that there was no significant difference between providers. After running the discrete-event simulation model, the patients' total time in system were analyzed as shown in Figure 7 and Figure 8. These boxplots compared the patients' total time in system for different monthly demand ratios.

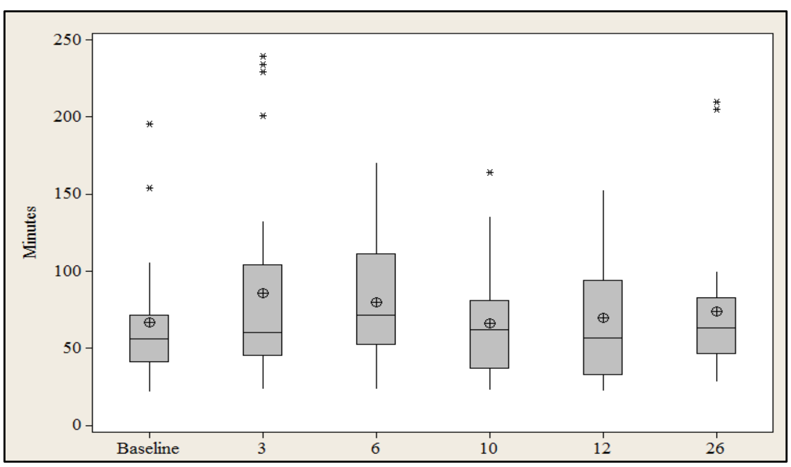

Figure 7: Time in System of New Patients

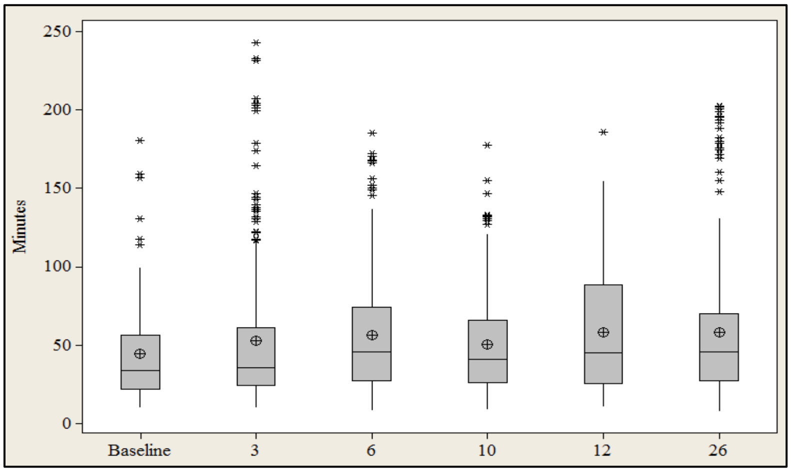

Figure 8: Time in System of Established Patients

5. Discussion

According to Figure 7 and Figure 8, for baseline, the average time in system is about 67 minutes of new patients (additional 27 minutes besides consulting) and 44 minutes (additional 22 minutes besides consulting) of established patients, which are both acceptable based on our assumption (additional 30 minutes besides consulting). In general, patients' total time in system will increase with overbooking; the average time in system in overbooking situation is longer than that of baseline. Furthermore, it is observed that average time in system fluctuates for both types of patients with different allocation policies (ratios of established patients' demand to new patients' demand).

When the ratio is 3 and the overbooking rate of new patients is 32.5%, system generates extra new patients that clinic cannot "consume" within acceptable time period; also with those "redundant" new patients, established patients have to wait for longer time, even over two hours in system as outliners in Figure 8. The situation is similar with the ratio of 6. These two situations illustrate that in these two allocation policies, system allocates excessive capacities to new patients and then results in long time in system and large variability, which decreases patients' satisfaction.

On the other hand, when the ratio is 26 and the overbooking rate of established patients is 86%, system generates extra established patients that exceeds the capabilities of clinic; and it results long time in system of both types of patients. According to the time in system of established patients, the variability increases dramatically with those outliners in Figure 8. Similarity, when the ratio is 12, the average patients' time in system and variability increases. These situations illustrate that with these two allocation policies, system allocates excessive capacities to established patients and then results in long time in system and large variability, which decrease patients' satisfaction. However, clinic rarely as outliners in allocation policy of ratio of 12; then it indicates that this policy actually decrease the variability comparing to that with ratio of 6.

When the ratio is 10 and the overbooking rate of new patients is 9% (81% of established patients), patients' time in system stays at the same level as baseline, in general. The fact that there is no significant increase in variability means that the system's performance is expected to be consistent. The allocation policy may therefore be seen as appropriate for clinic operations.

Since system dynamics model adjusts the capacity depending on the monthly demands of patients dynamically, it is highly possible that clinic will use the ratios that may increase time in system and results patients' dissatisfaction of clinic operational performance. Therefore, in order to maintain operations in clinic, ratio of allocating capacity of established patients to new patients should not fall all out of the range of 6 to 12. This range should be feedback to system dynamics so that the best overbooking policy within that as a constraint may be found to improve current model. In this way, the policies made by this feedback-based hybrid method consider not only the strategic goals, but also the practical operations in clinic.

6. Conclusion

Both system dynamics modeling and discrete-event simulation have found numerous applications in healthcare settings. However, much remains to be done to effectively harness each of these paradigms' strengths by combining them to address a single problem space. Through a case study, this paper attempted to demonstrate how harnessing those strengths could be achieved. Though overbooking is a widely used in practice to eliminate the negative effects of no-shows, it can also be used as an effective intervention strategy to reduce appointment delay. In this paper, an overbooking policy formulation problem was used to demonstrate how a feedback-based hybrid modeling and simulation method could work to improve both short and long term performance. The paper demonstrates how overbooking policies suggested a system dynamics model that is focused on the long term may be evaluated for day-to-day performance in the clinic using a discrete-event model. The analysis shows that not all policies that work for long term are good for the short term, and demonstrated how the discrete event model can impose policy constraints given a set operational performance goal such as the patients' total time in system. Such constraint should be fed back to the systems dynamics model such as an acceptable compromise may be reached.

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