Proceedings of the 2013 Winter Simulation Conference
R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, eds

A SIMULATION BASED ANALYSIS ON REDUCING PATIENT WAITING TIME FOR CONSULTATION IN AN OUTPATIENT EYE CLINIC

Xianfei Jin
Appa Iyer Sivakumar

Systems and Engineering Management
Nanyang Technological University
SINGAPORE

Sing Yong Lim

Ophthalmology
Tan Tock Seng Hospital
SINGAPORE

ABSTRACT

This paper presents a preliminary analysis to reduce patient waiting time for consultation in an outpatient eye clinic, using a data driven discrete event simulation model. This study is of interest and importance for a better understanding of the causes of patient long waiting in an actual clinic in an effort to reduce the patient waiting time for consultation. Several proposed strategies, such as pool scheduling of patients, uniform patient arrivals and improved process flow, have been studied. It is found that patients' irregular arrival pattern during a day is one of the main causes of the long waiting time. Analysis and recommendations for reducing patient waiting time at the eye clinic are provided in this paper. Simulation model of an eye clinic located in Singapore is used as the base case and the effects are quantified against the base model.

1 INTRODUCTION

Public outpatient health care services in Singapore and elsewhere are facing challenges as increasing demand for both primary care and specialty physicians as the baby boomer generation begins to enter its senior years. However, the health care resources, such as physicians and facilities, are not expanding accordingly. Hospitals or health services must therefore rely on improved flow control and better capacity allocation to minimize the negative effect of patient long waiting time.

In this paper we first analyze the patient arrivals and the actual waiting time from the historical data at an eye clinic in Singapore. We then provide a preliminary simulation based analysis of the effect of smooth patient arrivals (applying strategies in order to make patients arrive evenly), patient appointment scheduling, and modified process flow. There are many more variables in healthcare management, such as the availability of resources in a station that influence the patient waiting time. However, selected factors that are considered controllable by the clinic management has been chosen for this analysis. The variables such as resource expansion are the constraints of the corporate planning and outside the scope of this work.

The objective of the research is to identify the main causes of the prolonged patient waiting time for consultation through analyzing the impact of the selected controllable input variables on patient waiting time. Past historical data shows that 95 percentile waiting time at the clinic was about 2.5 hours. The objective is to help to reduce this overall patient waiting time for consultation. As an initial understanding, we expect this research to lead to simulation or analytical study in the future with more details and a narrower focus. This research is initiated with a vision to resolve the patient long waiting time for consultation, and it is the first step towards achieving significant impact on shortening patient waiting time for consultation.

In Section 2 the process steps at the eye clinic are presented, followed by a literature review in Section 3. The simulation model is discussed in Section 4, followed by proposed strategies to be studied in Section 5. Experimental results are discussed in Section 6. Finally, conclusions have been drawn in Section 7.

2 EYE CLINIC AND PROBLEM DOMAIN

Actual data over 26 days from the eye clinic in a hospital in Singapore are used for our analysis. This clinic currently serves an average of 415 patients per day. It has over 40 process stations, such as Registration, Visual Activity testing (VA), Consultation, Financial Counseling and Payment.

The clinic serves both subsidized and non-subsidized patients. For this study, only the subsidized part of the clinic will be investigated. In the subsidized clinic, there are two types of patient visits which are: (1) Sub-specialty Visit, where a specific doctor is assigned for consultation; (2) General Visit, where a patient is assigned to any doctor on a first available basis. Thus, there are two separate doctor groups in the consultation area, one for general patients and the other one for sub-specialty patients.

The clinic provides both consultation-centered service and test-centered service. As shown in Figure 1, about 97 % of the patients go to the registration counter when they arrive at the clinic (the percentage numbers shown above or below the arrows represent the proportion of the total patients who goes through this route). For the consultation-centered service, most of the patients in this clinic go through VA, Humphrey Visual Field testing (HVF) or Refraction testing before they see doctors. For the test-centered service, patients only do selected testing, for example Biometry. Since the consultation-centered service covers about 81% of total patients, and the capacity constraints are mainly located at the consultation stage, we investigate the clinic with the primary focus on the consultation-centered service in this paper, shown as simulation scope in Figure 1.

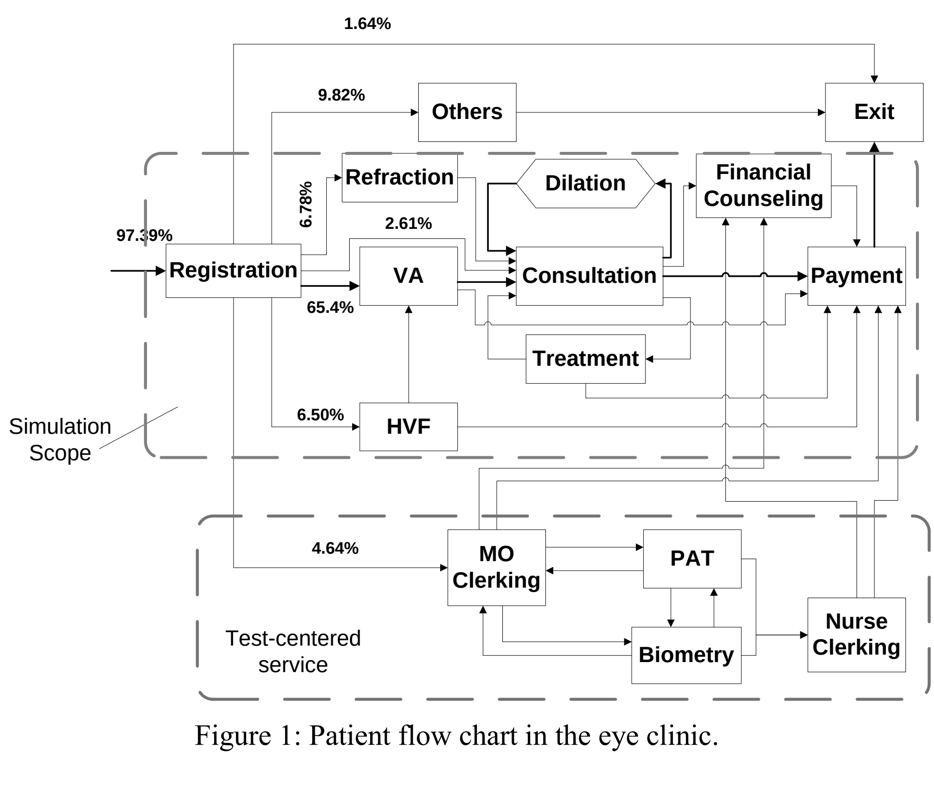

Figure 1: Patient flow chart in the eye clinic.

The clinic assigns appointments based on the number of available doctors in each clinic session. For example, the schedule of a doctor in one session (AM session is 9:00-11:30 or PM session is 14:00-16:30) is divided into 30 slots with 5 minutes each. The assignment of patient's appointment time is based on the beginning time of each slot. Most of the patients arriving to this clinic are with appointments. There are about 15 walk-in patients, which is around 7% of total arrivals, in each session who do not have appointments in one session. In the simulation model, we do not differentiate the walk-in patients. It is assumed that they have appointments as regular patients.

3 LITERATURE REVIEW

Various studies focusing on improving outpatient health care daily consultation in terms of reducing patient waiting time, physician idle time and physicians over time have been conducted. Most of the recent papers have investigated the patient appointment scheduling to improve the clinic performance. Cayirli and Veral (2003) and Lakshmi and Sivakumar (2013) gave an extensive review of the appointment scheduling research. In most of the analytical research on the appointment scheduling, an assumption that the patient arrives punctually if he/she will showed up for the appointment is made (Kaandorp and Koole 2007; Koeleman and Koole 2012; Millhiser et al. 2012). Harper and Gamlin (2003) studied the performance of different scheduling rules in the detailed simulation model of Ear, Nose and Throat outpatient department. Klassen and Yoogalingam (2009) integrate analytical method and simulation to find the appointment scheduling. The method can contribute good quality results while capturing uncertainties in the system.

Aside from research on appointment scheduling, this research examines patient arrival patterns to develop managerial policies to improve outpatient clinic performance. Some papers have studied similar problems. For example, Rising et al. (1973) analyzed the hourly arrival patterns in a day. Based on the arrival patterns, they scheduled more appointment patients during periods of low walk-in demand to smooth the overall daily arrivals. Swartzman (1970) focused on analyzing patient arrival process through a statistical method. It is suggested to use a time-varying poisson process to model the arrivals of unscheduled patients. It is evident that patient arrivals in a day vary through time. It is important to consider this phenomenon in the daily outpatient operations. Patient arrival patterns can be considered as a result of patients' behavior. Rockart and Hofmann (1969) firstly studied the behavior of physician and patient under different scheduling systems: pure block system and individual appointment system with pre-assigned or unassigned physicians. It is found that both physicians and patients tend to act more responsibly in the individual appointment system. Klassen and Rohleder (2004) considered using customers' motivation to reduce the peak demand in banking services.

Patient unpunctuality from the appointment also affect the patient arrival patterns. It is a challenge to model patient unpunctuality in the analytical analysis. A few papers have considered patient unpunctuality through simulation analysis. Fetter and Thompson (1966) examined the effect of patient load, patient unpunctuality and appointment intervals on patient waiting time through simulations. White and Pike (1964) studied the effect of patient unpunctuality on doctors' idle time and patients waiting time. Tai and Williams (2012) examed a probability distribution which maps patient unpunctuality in an appointment-driven outpatient clinic.

Similar to our paper, other research has also used simulation to analyze factors affecting the performance of an outpatient clinic. Swisher et al. (2001) used a factorial experiment to study the allocation of recourses. Zhu et al. (2012) reported that uneven appointment slots, early session start time and irregular calling sequence are main causes of long patient waiting time in a specific clinic. Jun et al. (1999) focused on the details in clinical simulation modeling.

Since the patient arrival patterns involve many uncontrollable factors such as patient behavior and traffic condition, it is a challenge to study the arrival patterns in an analytical way for daily operations. This paper is probably one of the first to study patient arrival patterns or unpunctuality in a simulation based study. It presents the importance of considering patient behavior in the appointment system, since that will cause serious system congestion in the clinic.

4 SIMULATION MODEL

4.1 Model Description

A discrete event simulation model of the eye clinic is constructed using FlexSim Healthcare. As discussed in Section 2, this eye clinic provides consultation-centered service. The objective of this research is to help the clinic management to find ways to make significant reduction in patient waiting time for consultation. In order to fulfill this, the model scope includes the process stations that preceded consultation rooms. Other stations providing services after consultation, such as Treatment station, Clerking station, Biometry station, Financial Counseling station and Payment counter are not modeled. Waiting time in the stations after the consultation process is not included in this preliminary study.

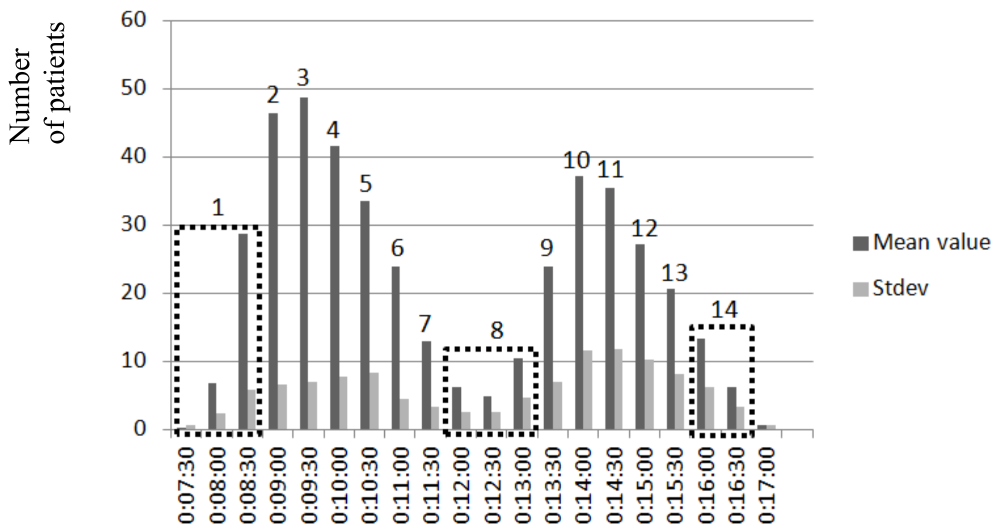

Figure 2: Number of patients arriving in each 30 minutes for 26 days.

To determine the patient arrival process, 26 working day clinic operation data has been analyzed. Figure 2 shows the mean/standard deviation value of the number of arrival patients in each 30 minute period. It is indicated that patient inter-arrival time varies in each period. The arrival is not characterized by a single distribution because the characteristic changes depend on time of day. A probability distribution is applied to generate patient inter-arrival times for each 30 minute period in Figure 2, except the beginning period (before 8:30), the ending period (15:30 onwards) and the period between 11:30-13:00. It is observed from the data that most of patient arrivals before 8:00 occurs in the period of 7:50-8:00. The inter-arrival time in this period is similar to the period of 8:00-8:30. Thus, a single probability distribution is used to model the period of 7:50-8:30. In the period of 11:30-13:00, a single distribution is applied to model the merged arrivals in these three 30-minute periods since the arrivals are rare. Similarly, a single distribution is assumed in the period beyond 16:00. As a result, 14 probability distributions are used to generate patient inter-arrival times as indicated in Figure 2.

Based on collected data, patient arrival is modeled on a probability of 0.65 for general patient and 0.35 for sub-specialty patient. If a patient is assigned as sub-specialty, he or she is assigned to a specific doctor in the sub-specialty doctor group randomly. On the other hand, a general patient will be served by the first available doctor in the general group. The number of consultation doctors is listed in Table 1 according to different sessions in a week. The patients are also assigned other characteristics based on past data and statistics, describing which type of tests they are required to go through, such as Refraction, VA and HVF. An abstracted model of the patient flow is shown in Figure 3. Another important characteristic is assigned to specify whether a patient does the dilation process during VA or after Consultation (as shown in Figure 3). The dilation process will take at least 30 minutes to have an effect, and dilation is required before patients can be seen by the doctor in the consultation room. Repeat visit patients will have their dilation done at the VA station rather than after consultation. Only first visit patients are required to be seen by the doctor first before having dilation done. After dilation, the first visit patient will then be seen again by the same doctor for a full consultation. Thus he/she will have two consultation sessions in this process.

Table 1： Allocation of consultation doctors during a week.

Session	Monday		Tuesday		Wednesday		Thursday		Friday	
	AM	PM	AM	PM	AM	PM	AM	PM	AM	PM
No. of doctors in general group	10	11	12	15	11	6	10	11	12	9
No. of doctors in sub-specialty group	4	3	5	4	4	5	3	6	4	5

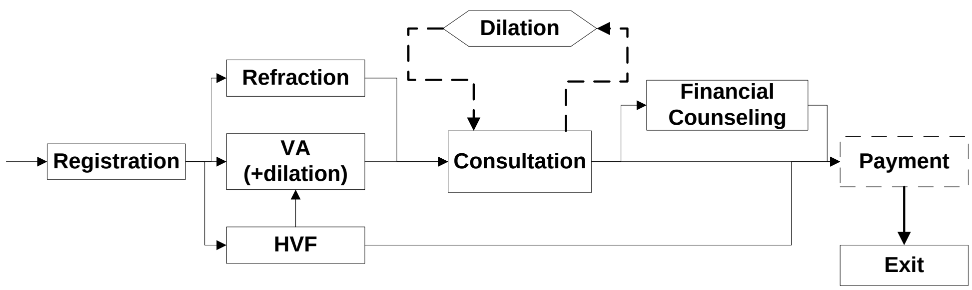

Figure 3: An abstract patient flow in the simulation model.

When patients are waiting for consultation, a general patient is called by the first available doctor in the general doctor pool, while a sub-specialty patient is served by a pre-specified doctor in the sub-specialty doctor pool. All patients are called based on First-Come-First-Serve (FCFS) rule in the simulation model. However, patients are called based on their appointment times in the clinic, and therefore at the actual clinic the patient with the earliest appointment time will be called first.

4.2 Model Assumptions

There are several assumptions made in the simulation model. It is assumed that the resources in the clinic (including staff and facilities) are either occupied by patients or available for patients. There will not be any other factor causing the unavailability of the resources, for example facility maintenance or staff rest. Secondly, we assume that the capacity at registration service is unlimited because there are adequate resources (self-service kiosks and several reception counters) having a short processing time. It is assumed that patients are called based on the FCFS rule because of the unavailability of exact appointment times for this research.

4.3 Model Input and Output

The purpose of the simulation study is to analyze the impact of various input parameters on selected measurements of patient waiting time. There are three major inputs to the simulation model as shown in Figure 4. The first one is the patient arrival patterns. In the basic simulation model, 14 different arrival processes are used to generate patient arrivals for different time periods through a simulation day. In the experiments, alternative types of arrival pattern are used as described in Section 5.2. The second input is the appointment schedule. A pooling schedule is applied in the sub-specialty group in the experiments. In the pooling schedule, patients are assigned to the first available doctor for consultation. The third input is the process flow. Two improved process flows have been tested in the experiments. The output of the simulation model is patients' waiting time for consultation, which is the duration between the registration time and the beginning time of patient's last consultation.

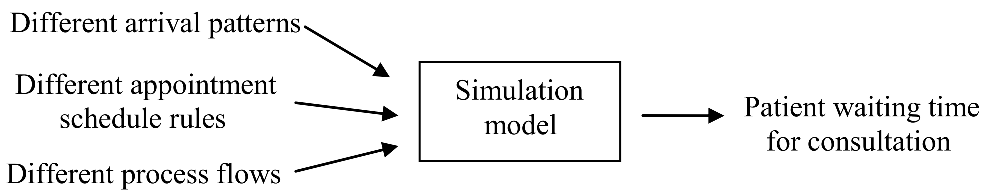

Figure 4: Input and output of the simulation model.

4.4 Key Performance Measures

Since the objective of this research is to find ways to reduce the waiting time for consultation, the performance measure is mainly based on the daily patient waiting time for consultation. In the clinic, patient waiting time (WT) for consultation is defined as the duration from the arrival time of a patient to the beginning time of the patient's last consultation (some patients go through one consultation process, while others go through two consultation processes). There are three commonly used measures for daily patient waiting time measurement in the clinic and they are the daily average waiting time, the median waiting time and the 95 percentile waiting time. The median/95 percentile waiting time is defined as the shortest waiting time of the 50%/95% of the all patients in a day. Among all these three, the 95 percentile waiting time is the primary performance measure for the clinic. The waiting time unit used throughout this paper is minute.

4.5 Model Verification and Validation

The model verification is done by systematically walking through the patient flows and analyzing the actual operation data. The flow and model logic are verified by the hospital staff using "walk through" technique.

The model is validated by comparing the outputs among actual system and simulation models. As shown in Model 1 from Figure 5, the actual arrivals from historical data are used in the simulation model. Since patient arrivals differ in different weekdays, several days of input are tested in the simulation model. In this model, six Wednesdays are simulated because they closely represent the clinic average performance. Using the actual arrivals, inter-arrival distributions are to simulate arrival process on Wednesdays. In Model 2, the base model is built with the generated inter-arrivals as the input. In this validation process, 30 instances are randomly generated for each simulation model, while the sample size of the actual historical data is 6.

In Table 2, it is seen that the outputs of two simulation models are relatively close to the actual system. It indicates that the inter-arrival distributions can truly represent the actual arrival process. It was also observed that the prediction of mean/median daily waiting time through the two simulation models is around 20% less than the actual output. The 95% percentile daily waiting time predictions are much closer to the actual output.

As there are three model outputs and a number of parameters in each model, for brevity, we will only demonstrate our model validation using the 95 percentile daily waiting time from data and simulation with actual arrivals as an example. Also the 95 percentile daily waiting time is the primary objective of the hospital. The objective is to construct a 90% confidence interval and therefore α is 0.1. Let $\bar{X}_1$ be the average value of observations of the system data and $\bar{X}_2$ be the average value of the observations of the model output. n_1 and n_2 are the sample size of the system and Model 2, respectively. That is,

$\bar{X}_1 = 164.51$, $\bar{X}_2 = 151.95$, $n_1 = 6$ and $n_2 = 30$.

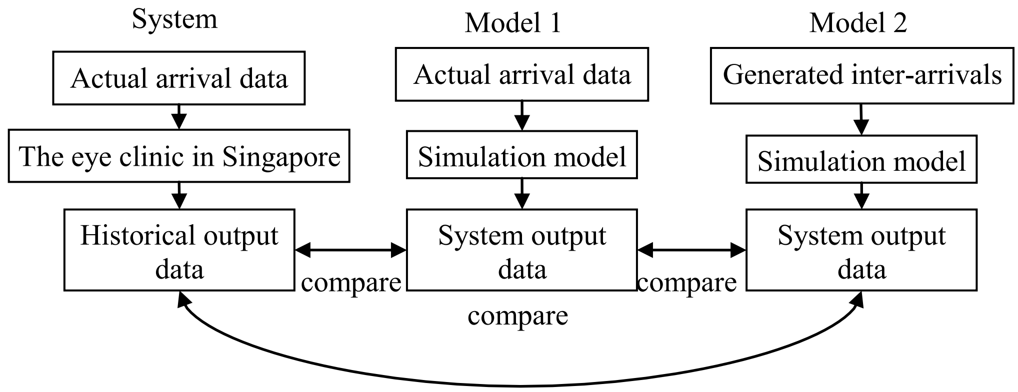

Figure 5: Validation based on correlated inspection.

Table 2: Comparisons among actual system outputs and simulation outputs from 30 replications.

	Mean daily WT (mins)		Median daily WT (mins)		95 percentile daily WT (mins)	
	Average	Stdev	Average	Stdev	Average	Stdev
Historical data from actual clinic	89.37	3.47	83.75	4.92	*164.51*	12.14
Simulation with actual arrivals	71.03	5.25	57.53	3.04	*151.95*	27.85
Simulation with generated arrivals	73.64	7.56	63.44	8.46	154.42	22.52

Assuming that the output of the actual data and the simulation model are subjected to two independent normal distributions, a hypotheses test is built to validate whether there is a difference between the mean values, u_1 and u_2 from the populations of the system output and Model 1's output, respectively.

$$H_0: u_1 - u_2 = 0.$$
$$H_1: u_1 - u_2 \neq 0.$$

The pooled estimator of the variance σ^2, denoted by ${S_p}^2$, is calculated by

$$S_p^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2} = 683.23$$

where the sample standard deviation $S_1 = 12.14$ and $S_2 = 27.85$.

The test statistic t_0 is obtained through

$$t_0 = \frac{\bar{X}_1 - \bar{X}_2}{S_p\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} = -1.074.$$

Therefore, using α = 0.1, we would fail to reject H_0 because $t_0 > -t_{0.05,(30+6-2)}$.

The hypothesis test result shows that the output between the actual data and the simulation model do not show significant differences. Other hypothesis tests on 95 percentile daily waiting time also indicate that the base model is sufficiently valid to do a preliminary analysis on the system.

5 STRATEGIES TO REDUCE PATIENT WAITING TIME FOR CONSULTATION

Several strategies are studied to reduce patient waiting time for consultation. These strategies are proposed based on improved schedules for physicians, better patient flow control and improved patient process flow. A summary of design of experiments is illustrated in Table 3. From the table, the independent variables list the factors that we are considering to propose strategies. For each independent variable, there are two levels, 1 is applied from the current actual eye clinic and 2 is proposed for investigation. Since the variables are independent and represent different aspects of the system, the study on the combinations of these variables are out of the scope of this paper. Four different simulation experiments have been tested and analyzed, details of each are discussed in the following sub-sections. The results of the experiments are presented in Section 6.

Table 3: Design of experiments on eye clinic simulation.

Independent variables	Levels 1	Levels 2
Appointment schedule rule	Dedicated doctors for sub-specialty patients	Pooling doctors for sub-specialty patients
Arrival Pattern	Historical arrival pattern	Smoothing arrival pattern
Change on process flow (1)	Registration is open at noon idle time	Registration is closed at noon idle time
Change on process flow (2)	Doctor in consultation room decides a patient need to have dilation or not	Set up a triage before consultation to estimate dilation requirement

5.1 Pooling Schedule for Sub-specialty Group

As mentioned, sub-specialty patients are assigned to their pre-specified doctors. Without considering the privileges of the sub-specialty patients, it is certain that the utilization of the doctors in sub-specialty group can be improved if a pooling schedule, in which a patient is assigned to the first available doctor, is applied. A series of simulation runs are performed to examine the effect of pooling doctors in sub-specialty group. The eye clinic validated pooling schedule as a feasible option.

In the simulation model with pooling doctors, a patient in sub-specialty group will not be assigned to a specific doctor in this group, but to any available doctor in this group.

5.2 Smoothing Patient Arrivals

In the clinic, the doctors in consultation rooms schedule identical time slots for every patient. As a result, there should be the same number of patients arriving in each half an hour. However, the number of patients arriving in each half an hour varies dramatically according to Figure 2. Figure 2 shows the actual half-an-hour arrivals in a day. There are two peaks in 9:00-9:30 and 13:30-14:00, respectively. Less patient arrivals occur when getting further away from these two peaks. This situation causes a heavy congestion in the system around these two peak hours. Patients have to wait for a long time before seeing the doctor. Therefore, there is an opportunity to reduce the waiting time for consultation by smoothing patient arrivals.

In the simulation model with smooth patient arrivals, the number of patient arrivals in half an hour is identical throughout the day from 8:00-11:30 in AM session and 13:00-16:30 in PM session. However, the arrival rate changes for different weekdays according to the actual scenario.

It is assumed that there are *n* doctors from either general group in one session. Generally, there are *c* identical appointments slots in a doctor's one-session-schedule. The inter-arrival time is $t_0 = (3 \times 60 + 30)/(c \cdot n)$ mins, which is calculated by the time duration of a session (3 hours and 30 minutes) divided by number of patients. Hence the *i*th patient in general group arriving time is, $t_i = (i-1)t_0$, assuming that the session starting time is 0. The inter-arrival time for sub-specialty patients having appointments with the same doctor is $t_1 = 210/c$ mins. Assuming there are *m* doctors in the sub-specialty group, the *i*th patient in sub-specialty group arriving time is, $t_i{}' = \lfloor (i-1)/m \rfloor t_1$.

5.3 Improved process flow

The following two strategies are proposed to improve the patient waiting experience through improved process flow in the clinic.

5.3.1 To Close Registration at Noon Idle Time

The consultation rooms at the clinic are open from 9:00 to 11:30 in the AM session and from 14:00 to 16:30 in the PM session. Although the consultation rooms are closed in the noon hour, it is observed that some patients also arrive and register during this period. In this situation, the patient arriving during the blank period will incur a long waiting time. It is suggested to close the registration counter between 12:00 and 13:00. Thus, the patient waiting can be improved.

From Figure 2, it is observed that only a few patients arrive during this period. It can be predicted that this strategy hardly affects the mean/median waiting time for consultation. However, some of the longest patient waiting times for consultation may be incurred by patients in this small category. It is an opportunity to reduce the 95 percentile patient waiting time for consultation.

5.3.2 To Avoid of Patient Second Consultation

In the normal procedure of the clinic, as stated in section 4.1 repeat visit patients have dilation done in the VA room before they are seen by the doctors, while first visit patients see doctors without a preliminary dilation. A doctor would require the patient to do dilation for a better examination. Thus, the patient will be required to leave the consultation room and have dilation done at the waiting area before seeing the doctor again when the eyes are fully dilated. Generally, it will take about 30 minutes for the dilation to take effect. In this case, the patient waiting time will be long because the patient has to queue twice to see the doctor, i.e. re-entry characteristics. System data at the clinic showed that about 36.54% of total patients have re-entry experience. In the simulation model, it is assumed that the portion of the first visit patients is 36.54%. If a triage station is set by a physician/optometrist for first visit patients before they go to consultation in order to determine whether they need to do dilation, the patients will only need one-time consultation.

Based on this assumption, a simulation model is built and many replications are conducted. In this assumption, the processing time of triage is not known yet, but it should be within a few minutes and with little variance. Thus the processing time of triage is considered as a part of the registration process in the simulation model in this preliminary research.

6 SIMULATION RESULTS

Table 4 summarizes the output statistics of the base model and four scenarios which reflect the strategies discussed in Section 5. For each scenario, the model is run for a day and for 30 replications. For a day run, there will be a daily mean/median/95 percentile patient waiting time for consultation. The average/standard deviation value is a statistic from 30-day replications. Figure 6 shows the 95 percentile daily waiting time on different scenarios.

6.1 Pooling Schedule for Sub-specialty group

Pooling should improve the doctor utilization rate in the sub-specialty group, and at the same time our conjecture is that the service level (patient waiting time for consultation) should be improved. Hypothesis tests are formed to compare the average value of the three estimators with the base model. However, the three waiting time measurements are not significantly reduced according to the results shown in Table 4 (row 2). This is because the non-subsidize group only serves a small portion of the total patients (35%). It is hard to create a significant effect on the overall patient waiting time for consultation.

Table 4: Summary results of simulation model.

	Scenario	Mean daily WT (mins)		Median daily WT (mins)		95 percentile daily WT (mins)	
		Average	Stdev	Average	Stdev	Average	Stdev
1	Base model	73.64	7.56	63.44	8.46	154.42	22.52
2	Pooling schedule for sub-specialty group	70.65	7.81	59.45	7.25	149.56	25.53
3	Smoothing patient arrivals	55.11	4.05	47.69	3.28	100.48	12.11
4	To close registration at noon idle time	70.17	6.82	61.92	6.33	139.37	18.32
5	To avoid patient second consultation	56.18	4.03	44.26	4.58	110.71	10.10

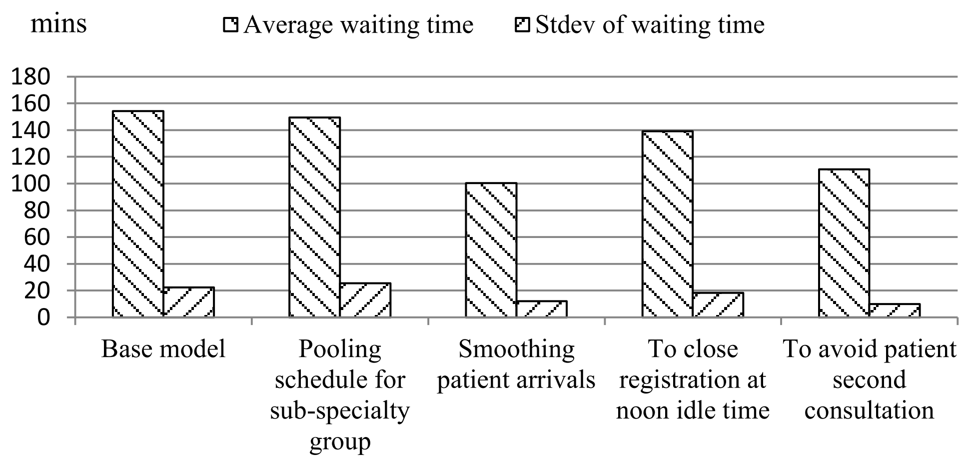

Figure 6: Results of 95 percentile daily waiting time on different scenarios.

6.2 Smoothing Patient Arrivals

Among all the other strategies, the effect of smoothing patient arrivals to reduce patient waiting time for consultation is one of the best as shown in Table 4 (row 3) and Figure 6. It reduces the average waiting time by about 30%. The standard deviation of the waiting time is also reduced by about 50%. It is indicated that the unpredicted patient arrival pattern causes high level of congestion in the system, which leads to long patient waiting.

In order to smooth the patient arrivals, the clinic may either provide incentives to punctual patients or impose penalties to patients who arrive early or late. A revised patient appointment strategy could be used to minimize or eliminate peak arrivals. For example, the clinic can schedule more patients at the beginning of the session and fewer patients at the peak hour.

6.3 To Close Registration at Noon Idle Time

Experiments are carried out to examine the effect of closing registration between 12:00 and 13:00. The comparisons of waiting times are listed in the Table 4. From the table, the mean and median value is not reduced significantly in the modified model. However, the 95 percentile of the waiting time has been reduced significantly as shown in Figure 6. This validates the assumption that part of the reasons for longest patient waiting in the system is caused by the patient arrival during this idle period.

6.4 To Set up a Triage to Avoid Patient Second Consultation

Table 4 (row 5) shows the results of the effect of one-time consultation for all patients. The effect is as good as that of smoothing patient arrivals as shown in Figure 6. Hypothesis tests are performed to compare the average value of the three estimators. It is known that the mean, median and 95% percentile daily waiting time have been significantly reduced if all patients only see doctors once without the break caused by dilation. In such a case, consultation capacity can be greatly saved.

It is suggested to set up a triage station for first visit patients to determine whether the patients need to do dilation before he/she sees the doctor. In this case, the patient waiting time for consultation can be reduced by about 30%.

7 CONCLUSION

The work demonstrated initial understanding particularly in the area of identifying the effect of some strategies on the patient waiting time for consultation in an outpatient eye clinic. In this paper, we demonstrate a discrete event simulation model of a subsidized part of an eye clinic and test strategies to reduce the patient waiting time for consultation.

The most significant finding from our analysis is that, if patients arrive according to their appointment time punctually, the patient waiting time for consultation can be reduced significantly, by about 30%. It indicates that patients' irregular arrival is the main cause of the congestion of the system and patients' long waiting time. In order to obtain smooth patient arrivals, we recommend scheduling patient appointments avoiding the crowded arrivals during peak hours, or applying incentives or penalties to regular patient arrivals. Another important finding is that if the re-entry to consultation caused by dilation can be avoided, the patient waiting time can be reduced to a level equivalent to the effect of smoothing patient arrivals. A triage process may be setup to determine whether a first visit patient needs to do dilation before consultation. To close the registration counter at noon idle time when consultation rooms are closed can help prevent patient waiting for the consultation rooms to open. This research has a limitation because of the assumption on patient calling sequence rule, which is FCFS in the simulation model.

In addition, this study highlights an opportunity for developing a method on scheduling patient appointments to smooth patient arrivals. This challenge is the focus of our ongoing research. The future work includes investigation of the impact of multiple strategies such as smoothing arrivals combined with improved process flow.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to Ms. Kucy Ping Ng at Tan Tock Seng Hospital for giving the opportunity to conduct this study and for the support in providing information and direction in the development of the simulation model and the associated analysis.

REFERENCES

Cayirli, T., and E. Veral. 2003. "Outpatient Scheduling in Health Care: A Review of Literature." *Production and Operations Management* 12:519-549.

Eldabi, T., R. J. Paul, and T. Young. 2007. "Simulation Modelling in Healthcare: Reviewing Legacies and Investigating Futures." *Journal of the Operational Research Society* 58:262-270.

Fetter, R. B., and J. D. Thompson. 1966. "Patients' Waiting Time and Doctors' Idle Time in the Outpatient Setting." *Health Services Research* 1:66-90.

Harper, P. R., and H. M. Gamlin. 2003. "Reduced Outpatient Waiting Times with Improved Appointment Scheduling: a Simulation Modelling Approach." *OR Spectrum* 25:207-222.

Jun, J. B., S. H. Jacobson, and J. R. Swisher. 1999. "Application of Discrete-event Simulation in Health Care Clinics: A Survey." *The Journal of the Operational Research Society* 50:109-123.

Kaandorp, G. C., and G. Koole. 2007. "Optimal Outpatient Appointment Scheduling." *Health Care Management Science* 10:217-229

Klassen, K. J., and T. R. Rohleder. 2004. "Using Customer Motivations to Reduce Peak Demand: Does It Work." *The Service Industries Journal* 24:53-69.

Klassen, K. J., and R. Yoogalingam. 2009. "Improving Performance in Outpatient Appointment Services with a Simulation Optimization Approach." *Production and Operations Management* 18:447-458.

Koeleman, P. M., and G. M. Koole. 2012. "Optimal Outpatient Appointment Scheduling with Emergency Arrivals and General Service Times." *IIE Transactions on Healthcare Systems Engineering* 2:14-30.

Lakshmi, C., and A. I. Sivakumar. 2013. "Application of Queueing Theory in Health Care: A Literature Review." *Operations Research for Health Care* http://dx.doi.org/10.1016/j.orhc.2013.03.002.

Millhiser, W. P., E. A. Veral, and B. C. Valenti. 2012. "Assessing Appointment Systems' Operational Performance with Policy Targets." *IIE Transactions on Healthcare Systems Engineering* 4:274-289.

Rising, E. J., R. Baron, and B. Averill. 1973. "A Systems Analysis of a University-health-service Outpatient Clinic." *Operations Research* 21:1030-1047.

Rockart, J. F., and P. B. Hofmann. 1969. "Physician and Patient Behavior under Different Scheduling Systems in a Hospital Outpatient Department." *Medical Care* 7:463-470.

Swartzman, G. 1970. "The Patient Arrival Process in Hospitals: Statistical Analysis." *Health Services Research* 5:320-329.

Swisher, J. R., S. H. Jacobson, J. B. Jun, and O. Balci. 2001. "Modeling and Analyzing a Physician Clinic Environment using Discrete-event (visual) Simulation." *Computers & Operations Research* 28:105-125.

Tai, G., and P. Williams. 2012. "Optimization of Scheduling Patient Appointments in Clinics using a Novel Modelling Technique of Patient Arrival." *Computer Methods and Programs in Biomedicine* 108:467-476.

White, M. J. B., and M. C. Pike. 1964. "Appointment Systems in Out-patients Clinics and the Effect of Patients' Unpunctuality." *Medical Care* 2:133-141,144-145.

Zhu, Z., B. H. Heng, and K. L. Teow. 2012. "Analysis of Factors Causing Long Patient Waiting Time and Clinic Overtime in Outpatient Clinics." *Journal of Medical Systems* 36:707-713.

AUTHOR BIOGRAPHIES

XIANFEI JIN is a Research Fellow in Nanyang Technological University (NTU). He has a Ph.D. in Operations Research from NTU (2012). His research interests include production scheduling, supply chain management and engineering optimization. His email address is jinxianfei@gmail.com.

APPA IYER SIVAKUMAR is an Associate Professor in the School of Mechanical and Aerospace Engineering (MAE) at Nanyang Technological University, Singapore. He is a Faculty Fellow of Singapore - Massachusetts Institute of Technology (MIT) Alliance (SMA-MST programme) and the Director of the NTU Undergraduate Research programme, URECA. His research interests are in the area of Systems Engineering, Health Systems, Operations Research, Optimization, Advanced Manufacturing Systems engineering, Discrete Event Simulation, Scheduling, Logistics and Supply chain design. His email address is msiva@ntu.edu.sg.

SING YONG LIM is currently the Assistant Operations Manager with the National Healthcare Group Eye Institute @ Tan Tock Seng Hospital, Singapore and has been with the institution for coming 7 years. Her experiences and responsibilities include overseeing the operations of the eye clinics in Tan Tock Seng Hospital and administrator for the Primary Eye Care arm of the institute. She is also the coordinator for new IT or electronic systems for the institute, which includes electronic medical records, appointment systems, electronic queue management systems for operational efficiency. Her email address is sing_yong_lim@ttsh.com.sg.