Available online at http://www.i4e2.com/journal

An I^4e^2 publication

Journal of Operations and Logistics
Volume 2, Issue 2, 2008

Simulating Staffing Needs for Consultation in Hospital Clinics *

Arun KUMAR [a], Sung J. SHIM [b], Ayliana PHE [c]

[a] *School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore*

[b] *Stillman School of Business, Seton Hall University, South Orange, New Jersey, USA*

[c] *Tan Tock Seng Hospital, Singapore*

Received October 31, 2007, Accepted June 2, 2008
Reviewed and Accepted by F. Dexter and N. Meskens

Abstract

As healthcare costs increase, there is a need for hospitals to look for ways to contain costs and to achieve a higher efficiency in their clinics without sacrificing quality. Just as many businesses have successfully reduced costs and gained competitive advantage by reengineering business processes, hospitals are now beginning to adopt a process-oriented approach and redesign the way certain processes are carried out to achieve cost containment and efficiency. Using computer simulation, this study assessed the efficiency of the consultation process in hospital clinics and recommended the optimal number of doctors, at which doctors as well as consultation rooms could be most efficiently utilized and patient wait times could be reduced. The results show that computer simulation is an effective tool supporting decisions on needs for doctors in the consultation process in hospital clinics.

Key words: Business process reengineering, Health services, Human resources, Manpower planning, Simulation

---

1 Introduction

Organizations reengineer their business processes to improve efficiency, to contain costs and to stay competitive in the marketplace. With escalating healthcare costs, hospitals also seek ways to provide quality healthcare services while containing costs. Hospitals have traditionally emphasized breakthroughs in healthcare technology to stay competitive. As competition among hospitals continues to intensify, however, patients may perceive little difference in the healthcare technology used by different hospitals. Consequently, hospitals are beginning to understand that process reengineering can be a better solution to achieve competitive advantage. Just as many businesses successfully reduce costs and gain competitive advantage by reengineering their business processes, hospitals can reengineer the way certain healthcare processes are carried out to achieve efficiency and cost containment. Computer simulation that has proven successful in improving various business processes can also be an effective tool in the search for more efficient processes in hospitals.

* Corresponding author A. Kumar. Tel. 65-67906181. Fax 65-6791-1859.
Email addresses: makumar@ntu.edu.sg (Arun KUMAR), shimsung@shu.edu (Sung J. SHIM), phe_ayliana@yahoo.co.uk (Ayliana PHE).

This paper describes a case study undertaken at Tan Tock Seng Hospital (referred to as 'the Hospital' hereafter for brevity) in Singapore. Using computer simulation, the study assessed the efficiency of the consultation process in two specialty clinics for outpatients in terms of patient wait times and utilization of doctors and consultation rooms involved in the consultation process, and recommended the optimal number of doctors needed for the process in each clinic. The results of the study will prove helpful to those who are considering reengineering and improving the consultation or other similar processes in hospital clinics.

2 Computer simulation in healthcare

Computer simulation involves modeling processes. Simulation models enable analysts to study how a system reacts to conditions that are not easily or safely applied in a real-world situation and to study how the working of an entire system can be altered by changing individual parts of the system [38]. The real power of simulation is fully realized when it is used to study complex systems [26]. Healthcare is a dynamic system with complex interactions among various components and processes. Furthermore, healthcare management operates in an environment of aggressive pricing, tough competition and rapidly changing guidelines. To meet these challenges, healthcare management must respond quickly to identify critical system processes, recognize all relevant resources, access real-time information and analyze 'what if' cases [42].

While there are many applications of computer simulation to healthcare management and operations, we may classify these into two groups: (1) applications to healthcare systems at the various levels of communities, regions or the nation, and (2) applications to specific operations, processes or services in healthcare institutions. The first group includes applications intended to study the provisions of mental health, public health, health reform or healthcare workforce, often with policy implications. For example, Agnihotri et al [2], De Vries et al [14], Elveback and Varma [16], Liyanage and Gale [33], Jacobson and Sewell [24], Naylor et al [35], Wang [45], Zaric [49], and Zenios [50] illustrate the use of simulation and queuing theory for various health policy analyses. The second group, which is relevant to the case study of this paper, includes applications intended to improve facility design, staffing and scheduling and to reduce patient wait times and operating costs [3].

Recently, a good bibliographic survey on medical staff rostering problems has appeared [13]. Several studies have utilized mathematical programming techniques to assist in finding efficient staff schedules [6], [9], [12]. Callahan [11] and Hariharan et al [20] have highlighted the effects of problem-based scheduling on patient waiting and staff utilization of time in hospital clinics. Numerous previous studies have been carried out to improve the efficiency of scheduling in health care systems [15], [17], [19], [28], [32], [36], [46]. Further, staffing needs of whole hospitals [2] have been modeled using queuing theory. However, in this paper we focus on the application of queuing models to an outpatient-appointment environment.

Previous research has sought to balance between the patient's waiting times with the physicians in an outpatient environment. A large percentage of research in this area has assumed that a physician's time is more valuable compared to a patient's. Hence the main consideration in improving efficiency of the scheduling of appointments is to not keep the doctor waiting before the next patient arrives. Quite a number of papers have been based on the pioneer work of Bailey [8] using mathematical and operational techniques such as queuing theory [10], [23], simulation [1], [7], [21], [30], [43], [22] and soft systems modeling.

Due to the highly complex nature of medical clinics where the different patients require varying modes of treatment, numerous investigators have utilized simulation as a flexible optimization method which can represent each patient type's distinct needs and flows, at the same time taking into account the arrival patterns, the variance in length of treatment and consultations and exit patterns. Anderson et al [4], Duraiswamy et al [16], Flagle [18], Hearn and Bishop [22], Jeans et al [25], Levy et al [31], Rauner [39], Kumar et al [27] and Wijewickrama [48] illustrate the use of simulation for improving hospital staffing and scheduling and to reduce patient wait times and operating costs. As staffing actions are usually slow to evolve and long term in nature, simulation can provide the opportunity to evaluate different alternatives at substantially lower costs with fewer risks. For example, Arvy and Morin [5] use simulation to study the effects of staffing adjustments on patient throughput within a clinic. Wilt et al [47] show that simulation can provide significant insight in a study of optimal staffing and facility design of an outpatient clinic. Uyeno uses simulation in determining the most efficient healthcare team compositions for different demand levels at a pediatric clinic [44]. Kumar and Shim [27] use simulation in searching for the optimal number of healthcare assistants needed for delivery of surgical instruments to operating rooms in a hospital. A common objective of these simulation models is to assist with staffing in various healthcare settings. The case study described below attempted to extend this line of studies by considering utilization of both entities and resources involved in the consultation process in hospital clinics. Nowhere in the literature, however, there was a model of computer simulated staffing studies by considering both entities and resources involved in the consultation process specific to outpatient clinics. The simulation based approach has advantages over conventional methods, especially when the manpower planner wishes to pre-evaluate alternative decision options by simulating staffing implications under alternative scenarios.

3 Case study

3.1 Background

The Hospital runs eighteen specialty clinics for outpatients. For the case study of this paper, we examined the consultation process in two specialty clinics for outpatients: general medicine (GM) clinic and rheumatology, allergy and immunology (RAI) clinic. The GM clinic treat patients in the areas of multi-system illnesses, undifferentiated medical problems, hypertensions and lipids obstetric medicine, vascular medicine, hematology and palliative care. The RAI clinic treats patients in the areas of arthropathies, connective tissue diseases, soft tissue rheumatism, rheumatic diseases, drug, food and insect venom allergies, anaphylaxis, urticaria and angioedema, allergic rhinitis and asthma, atopic eczema, and investigations. A total of 548 patients that were treated in the GM and RAI clinics, respectively, were surveyed in a five-day work-week during September 2004 by patient type. Out of these, the repeat cases at GM and RAI were 78% and 97%, respectively, which had previously visited the clinic. The patients were given appointment times before consultation. The clinics generally had peak hours from 0900 to 1200 hours and 1400 to 1600 hours where the patient appointments were the highest. The clinic was closed for lunch at 1300-1400 hours.

3.2 Modeling the consultation process

The main objective of simulation in this study was to model the consultation process and determine the optimal number of doctors needed in the process in each clinic in terms of three efficiency measures: (1) patient wait times, (2) utilization of doctors, and (3) utilization of consultation rooms. In the context of the consultation process in the clinics, doctors are considered as being utilized while they are attending in consultation rooms, and otherwise, they are considered as being idle. Also, consultation rooms are considered as being utilized while they are occupied by doctors, and otherwise, they are considered as being idle.

Fig. 1 shows the consultation process in the clinics, including the entities, resources and locations involved in the process. An entity refers to an object or person that a simulation model processes. There is one type of entities (patients) in the simulation model. A location represents a fixed place in the system where entities are routed for processing or some other activity or decision. The simulation model has four types of locations (registration counters, consultation rooms, diagnostic laboratories, and payment counters). Both the GM clinic and the RAI clinic have two registration counters: one automated counter for repeat patients and the other counter manned by a counter staff. The GM clinic has sixteen general consultation rooms and two subspecialty rooms used for gastric motility tests and breast care nurses. The RAI clinic has nine consultation rooms. Both the GM clinic and the RAI clinic have two payment counters located near the waiting area and each payment counter is serviced by a cashier. A resource is a person, piece of equipment or some other device used for one or more of the following functions: treating and moving entities, assisting in performing tasks for entities at locations, and performing maintenance on locations or other resources. There are three types of resources (nurses, doctors and cashiers) in the simulation model.

Three queues are formed in the consultation process in the clinics: at registration counters, for consultation by doctors, and at payment counters. Only at registration counters is a physical queue where patients wait in line. The consultation queue is operated using queue numbers given at registration counters and displayed outside of consultation rooms. The payment queue number is different from the consultation queue number. After the consultation, patients wait at the main waiting area until they are routed to payment counters.

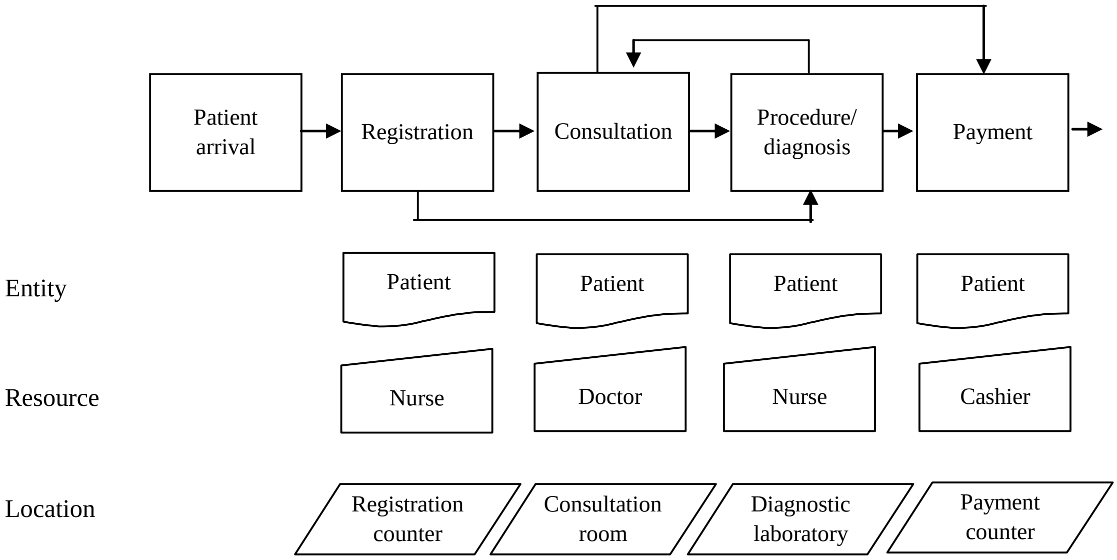

Fig. 1. Consultation process in the clinics

3.3 Data

For the simulation in this study, we used historical data collected in a five-day work-week (Monday to Friday) during September 2004. Inter-arrival times of patients in the GM and RAI clinics during the period were found to be exponentially distributed with mean value of 4.6 minutes and 7 minutes, respectively. Also, service times in the GM and RAI clinics during the period were found to be Erlang-distributed with mean value of 11.7 minutes and standard deviation of 6.64 and mean value of 13 minutes and standard deviation of 5.73, respectively. Table 1 shows the number of doctors and utilization of consultation rooms in the GM and RAI clinics on each working day during the period.

Table 1
Number of doctors and utilization of consultation rooms

	Monday	Tuesday	Wednesday	Thursday	Friday	Average
GM clinic						
Number of doctors	17	5	8	4	3	7.4
Utilization of consultation rooms	100%	33%	53%	27%	20%	47%
RAI clinic						
Number of doctors	6	4	4	1	0	3
Utilization of consultation rooms	67%	44%	44%	11%	0%	33%

3.4 Running and validating the simulation model

We constructed the simulation model using Arena™ simulation software. The simulation model was run for 25 independent replications of 30 days, with each replication using an additional warm-up period of 3 days. The warm-up period, which is set for the simulation run to eliminate any bias at the early stage of the process, was determined according to Welch's moving average procedure described in Law and Kelton [29]. The run length and number of independent replications of the simulation were also determined based upon the tests of normality and independence proposed by Law and Kelton [29]. The simulation results presented in the following section are based upon the average results of the 25 independent replications.

Validation is the process of determining whether the simulation model is a useful or reasonable representation of the real system [37]. Absolute validation is usually impossible because the simulation is at best an approximation of the real system, and the most definitive method is to compare the output data from the simulation with the actual data from the existing system using formal statistical analyses as confidence intervals [41]. In validating the simulation model of this study, we calculated the confidence intervals of the simulation outputs at 95% (α = 0.05) confidence level and compared them with the actual values obtained from the Hospital. We also compared the simulation outputs with the results from queuing models whenever possible. In addition, we verified the architecture of the simulation model with hospital staff before the simulation runs and showed the simulation results to hospital staff after the simulation runs to ensure that the simulation results are reliable.

4 Results and discussion

We ran the simulation model in six different cases with three to eight doctors available in each clinic, respectively. Each case was built on a common foundation or base model. The only variable that changed between cases was the number of doctors, and all other variables were held constant.

4.1 Results on the GM clinic

Table 2 shows the simulation results on patient wait times in the GM clinic. There is a big difference between the case of three doctors and the other cases of four or more doctors. But there is no big difference among the cases of four or more doctors. These results suggest that four doctors would be enough to allow short wait times for patients. Table 2 also shows the 95% confidence intervals of the simulated estimates against the actual values. All confidence intervals, except those in the cases of six or more doctors, include the actual values. The actual value in the case of six doctors is outside the respective confidence interval, but the absolute difference is reasonably small and tolerable. Thus, the simulation model seems to be capable of reproducing the patient wait times in the consultation process. The confidence intervals of the simulation estimates are not compared with the actual values in the cases of seven or eight doctors. This is because these cases were never implemented, and so, the actual values were not available. In addition, Table 2 compares the simulation estimates with the results from queuing models. There is no big difference between the simulation estimates and the results from queuing models, which can help reconfirm the validity of the simulation model with respect to the patient wait times.

Table 2
Patient wait time in the GM clinic (minutes)

Number Of doctors	Simulation mean[(a)]	Confidence interval α = 0.05 (95%) Mean$\pm t_{n-1,\alpha/2}Sx/\sqrt{n}$	Actual mean	Queuing Mean[(b)]	(b)-(a)
3	14.56	(13.12, 15.99)	15.96	18.54	3.98
4	1.82	(1.33, 2.30)	2.25	2.64	0.82
5	0.54	(0.38, 0.69)	0.60	0.66	0.12
6	0.12	(0.09, 0.14)	0.15	0.18	0.06
7	0.03	(0.03, 0.04)	n.a.	0.04	0.01
8	0.01	(0.01, 0.01)	n.a.	0.01	0.00

Table 3 shows the simulation results on utilization of doctors in the GM clinic. The utilization level of doctors decreases from 85.4% to 30.3%, as the number of doctors increases from three to eight. Table 3 also shows the 95% confidence intervals of the simulated estimates against the actual values. All confidence intervals, except those in the cases of seven or eight doctors where the actual values were not available, include the actual values. Thus, the simulation model seems to be capable of reproducing the utilization of doctors in the consultation process. In addition, Table 3 compares the simulation estimates with the results from queuing models. There is no big difference between the simulation estimates and the results from queuing models, which can help reconfirm the validity of the simulation model with respect to the utilization of doctors in the consultation process.

Table 4 shows the simulation results on utilization of consultation rooms in the GM clinic. While the utilization level of consultation rooms is generally low and does not change much as the number of doctors changes, the highest utilization of consultation rooms is achieved in the case of six doctors. All the 95% confidence intervals, except those in the cases of seven or eight doctors where the actual values were not available, include the actual values. Thus, the simulation model seems to be capable of reproducing the utilization of consultations rooms in the consultation process.

Table 3
Utilization of doctors in the GM clinic

Number Of Doctors	Simulation mean(a)	Confidence interval $\alpha = 0.05$ (95%) $\text{Mean} \pm t_{n-1,\alpha/2} Sx/\sqrt{n}$	Actual mean	Queuing Mean(b)	(b)-(a)
3	0.854	(0.751, 0.956)	0.86	0.847	-0.007
4	0.629	(0.554, 0.703)	0.58	0.635	0.006
5	0.519	(0.456, 0.581)	0.47	0.508	-0.011
6	0.451	(0.405, 0.496)	0.41	0.423	-0.028
7	0.350	(0.310, 0.390)	n.a.	0.363	0.013
8	0.303	(0.263, 0.343)	n.a.	0.317	0.014

Table 4
Utilization of consultation rooms in the GM clinic

Number of doctors	Simulation Mean	Confidence interval $\alpha = 0.05$ (95%) $\text{Mean} \pm t_{n-1,\alpha/2} Sx/\sqrt{n}$	Actual Mean	Queuing Mean(b)	(b)-(a)
3	0.160	(0.138, 0.181)	0.157	n.a.	n.a.
4	0.157	(0.138, 0.175)	0.160	n.a.	n.a.
5	0.162	(0.139, 0.184)	0.172	n.a.	n.a.
6	0.169	(0.147, 0.190)	0.181	n.a.	n.a.
7	0.153	(0.136, 0.170)	n.a.	n.a.	n.a.
8	0.151	(0.132, 0.169)	n.a.	n.a.	n.a.

Fig. 2 combines the results on patient wait times and utilization of doctors and consultation rooms in the GM clinic. Based upon the results, the GM clinic is recommended to utilize either four or six doctors. In the case of four doctors, the utilization levels of both doctors and consultation rooms are relatively high at 62.9% and 15.7%, respectively, while the patient wait time decreases significantly to 1.82 minutes. In the case of six doctors, the utilization level of consultation rooms is the highest at 16.9%, while the utilization level of doctors is relatively low at 45.1% and the patient wait time is only 0.14 minutes. In either case, the utilization level of consultation rooms is still low, and so, the GM clinic is also recommended to use some of its consultation rooms for other purposes or reduce the number of consultation rooms.

4.2 Results on the RAI clinic

Table 5 shows the simulation results on patient wait times in the RAI clinic. The results are similar to those on patient wait times in the GM clinic, in that there is a big difference between the case of three doctors and the other cases of four or more doctors, and there is no big difference among the cases of four or more doctors. These results suggest that four doctors would be enough to allow short wait times for patients. Since the simulation cases were not actually implemented in the RAI clinic, no actual values to compare with the simulation estimates were available. But no big difference is found between the simulation estimates and the results from queuing models, which can help ensure the validity of the simulation model with respect to the patient wait times in the RAI clinic.

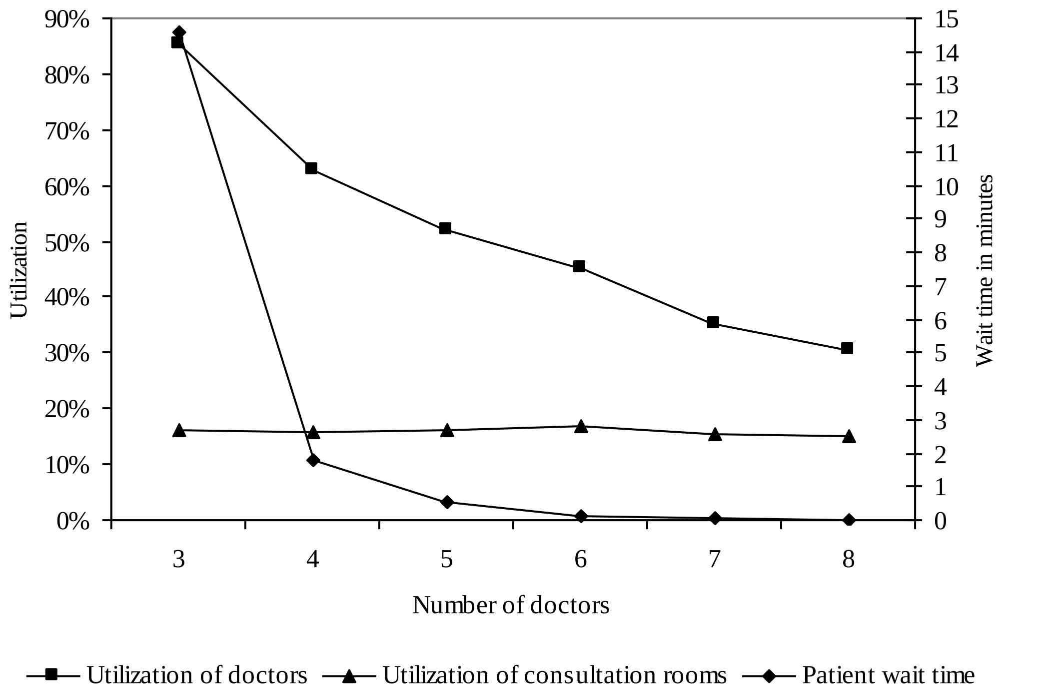

Fig. 2. Patient wait time and utilization of doctors and consultation rooms in the GM clinic

Table 5
Patient waiting time in the RAI clinic (minutes)

Number of doctors	Simulation mean[(a)]	Confidence interval $\alpha = 0.05$ (95%) Mean$\pm t_{n-1,\alpha/2}Sx/\sqrt{n}$	Actual mean	Queuing Mean[(b)]	(b)-(a)
3	3.180	(2.820, 3.480)	n.a.	4.260	1.080
4	0.600	(0.480, 0.720)	n.a.	0.840	0.240
5	0.480	(0.420, 0.540)	n.a.	0.600	0.120
6	0.060	(0.048, 0.066)	n.a.	0.120	0.060
7	0.036	(0.030, 0.036)	n.a.	0.042	0.006
8	0.006	(0.000, 0.006)	n.a.	0.006	0.000

Table 6 shows the simulation results on utilization of doctors in the RAI clinic. The results are similar to those on utilization of doctors in the GM clinic. The utilization level of doctors decreases from 60.4% to 22.7%, as the number of doctors increases from three to eight. Table 6 also compares the simulation estimates with the results from queuing models. There is no big difference between the simulation estimates and the results from queuing models, which can help reconfirm the validity of the simulation model with respect to the utilization of doctors in the RAI clinic. Table 7 shows the simulation results on utilization of consultation rooms in the RAI clinic. The utilization level of consultation rooms does not change much, as the number of doctors changes.

Fig. 3 combines the results on patient wait times and utilization of doctors and consultation rooms in the RAI clinic. Based upon the results, the RAI clinic is recommended to utilize three doctors. In the case of three doctors, the utilization levels of both doctors and consultation rooms are the highest at 60.4% and 21.5%, respectively, while the patient wait time is 3.18 minutes. As in the GM clinic, the utilization level of consultation rooms is generally low in the RAI clinic, and so, the RAI clinic is also recommended to use some of its consultation rooms for other purposes or reduce the number of consultation rooms.

Table 6
Utilization of doctors in the RAI clinic

Number of doctors	Simulation mean(a)	Confidence interval $\alpha = 0.05$ (95%) $Mean \pm t_{n-1,\alpha/2} Sx/\sqrt{n}$	Actual mean	Queuing Mean(b)	(b)-(a)
3	0.604	(0.529, 0.678)	n.a.	0.618	0.014
4	0.460	(0.414, 0.505)	n.a.	0.463	0.003
5	0.365	(0.325, 0.400)	n.a.	0.370	0.005
6	0.294	(0.265, 0.322)	n.a.	0.309	0.015
7	0.257	(0.228, 0.285)	n.a.	0.264	0.007
8	0.227	(0.204, 0.250)	n.a.	0.231	0.004

Table 7
Utilization of consultation rooms in the RAI clinic

Number Of doctors	Simulation mean(a)	Confidence interval $\alpha = 0.05$ (95%) $Mean \pm t_{n-1,\alpha/2} Sx/\sqrt{n}$	Actual mean	Queuing Mean(b)	(b)-(a)
3	0.215	(0.192, 0.237)	n.a.	n.a.	n.a.
4	0.192	(0.169, 0.214)	n.a.	n.a.	n.a.
5	0.187	(0.167, 0.206)	n.a.	n.a.	n.a.
6	0.187	(0.170, 0.204)	n.a.	n.a.	n.a.
7	0.196	(0.173, 0.218)	n.a.	n.a.	n.a.
8	0.196	(0.178, 0.213)	n.a.	n.a.	n.a.

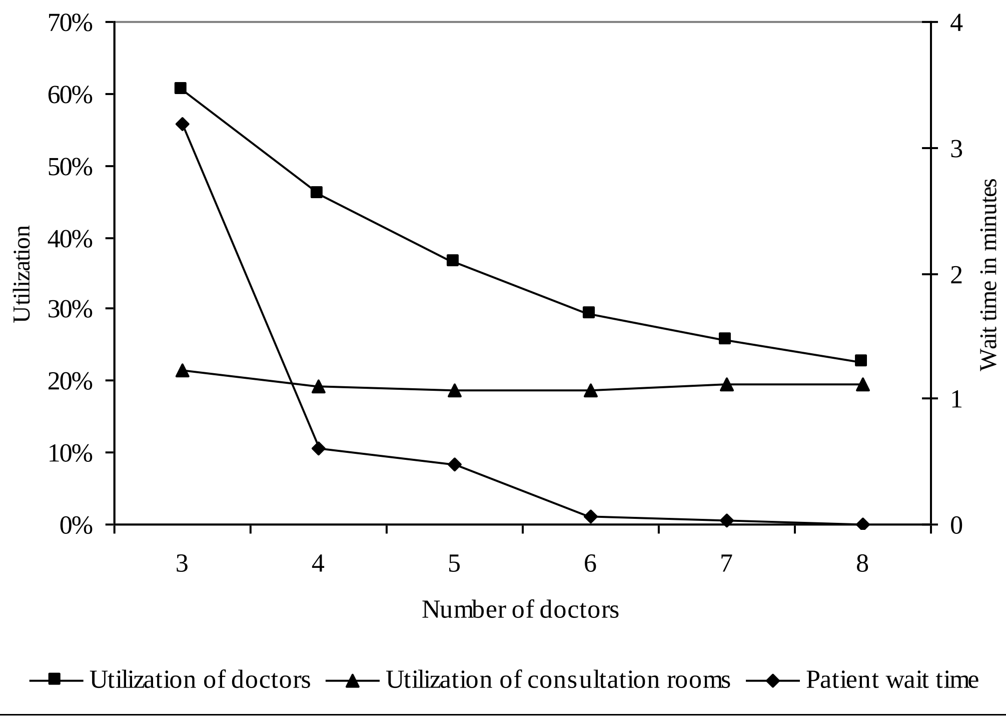

Fig. 3. Patient wait time and utilization of doctors and consultation rooms in the RAI clinic

4.3 Sensitivity analysis

Sensitivity analyses were used to learn how clinic staffing, patient load, arrival time interval for patients and variability influenced the patient wait time and number of patients in the queue.

Looking at the average number of patients waiting in the consultation queues of GM and RAI clinics, Table 8 and Table 9 show results for the average number in queue along with the 95% confidence intervals of the simulated estimates. Increasing the number of doctors in any clinic decreased the number of patients waiting in the queue and variably affected the patient load and the patient total time in the clinic. The simulation model was used to experiment with several patient arrival intervals to gain a sense of how busy doctors were at various times during the day. The model assumed a Poisson arrival process and used the percentage distribution of hourly arrivals. The number of patient–doctor encounters was high from 09:00 to 10:00 hours and 14:00 to 15:00 hours. There was a peak day on Monday and a sharp dip in appointments on Tuesday.

Table 8
Average number of patients waiting in the consultation queue in the GM clinic

Number Of doctors	Simulation mean$^{(a)}$	Confidence interval $\alpha = 0.05$ (95%) Mean$\pm t_{n-1,\alpha/2} Sx/\sqrt{n}$	Actual mean	Queuing Mean$^{(b)}$	(b)-(a)
3	2.961	(2.67, 3.24)	n.a.	3.827	0.866
4	0.262	(0.23, 0.29)	n.a.	0.582	0.32
5	0.134	(0.125, 0.146)	n.a.	0.142	0.008
6	0.032	(0.026, 0.038)	n.a.	0.037	0.005
7	0.007	(0.0065, 0.0075)	n.a.	0.009	0.002
8	0.0003	(0.0002, 0.0003)	n.a.	0.0002	0.000

Table 9
Average number of patients waiting in the consultation queue in the RAI clinic

Number Of doctors	Simulation mean$^{(a)}$	Confidence interval $\alpha = 0.05$ (95%) Mean$\pm t_{n-1,\alpha/2} Sx/\sqrt{n}$	Actual mean	Queuing Mean$^{(b)}$	(b)-(a)
3	0.456	(0.410, 0.501)	n.a.	0.613	0.157
4	0.098	(0.087, 0.109)	n.a.	0.121	0.023
5	0.019	(0.016, 0.021)	n.a.	0.026	0.007
6	0.004	(0.0035, 0.0044)	n.a.	0.005	0.001
7	0.0008	(0.0007, 0.0009)	n.a.	0.0011	0.000
8	0.0002	(0.00018, 0.0002)	n.a.	0.0002	0.000

The simulation model was tested and evaluated at the outpatient clinics of the Hospital. By better matching available space with physicians, waiting times for patients were shortened [40]. Thus, the results for both GM and RAI clinics show that scenario analysis based on computer simulation is an effective decision support tool for optimally staffing consultation rooms in hospital clinics. This study confirms computer simulation as an effective manpower decision support system. The simulation model enables manpower planners to respond objectively and promptly to requests for more consultants/physicians or consultation rooms by hospital clinics.

5 Conclusion

Using computer simulation, this study assessed the needs for doctors in the consultation process in two hospital clinics in terms of patient wait times and utilization of doctors as well as consultation rooms. The simulation results were validated with the actual values as well as the results from queuing models. The 95% confidence intervals of the simulation outputs included the actual values in most cases and the simulation outputs were consistent with the results from queuing models, indicating that the simulation model was capable of reproducing the consultation process in the clinics with respect to the patient wait times and the utilization of doctors and consultation rooms. The analysis showed that there were opportunities for improvement in the utilization of resources in each clinic, especially of the consultation rooms. The results from both the queuing and simulation models were compared and it was found that the simulation model was consistent with queuing theory assessment for both clinics. Based upon the simulation results, we recommended the optimal numbers of doctors needed for the consultation process in each clinic, at which the utilization of doctors and consultation rooms and the patient wait times could be balanced. Thus, the main objectives in this study of modeling the consultation process and determining the optimal number of doctors needed in each clinic in terms of three efficiency measures were achieved.

The model had been extensively tested and evaluated in the outpatient clinics of the Hospital. The system was considered to be very promising for facilitating the staffing needs and improving the efficiency of resource utilization. Better use of consultation rooms had allowed all the specialist outpatient clinics fit in 40 more patients a day [40]. Waiting times at some specialist outpatient clinics of the Hospital had been trimmed, with extra patients getting appointments. This was achieved without getting extra doctors – just a better way of using the Hospital’s consultation rooms [40].

A couple of limitations are recognized in this case study. First, the simulation did not consider the effects of the varying number of doctors on costs, flexibility and quality of the consultation process. Utilizing more doctors may incur increased costs. Increasing the utilization levels of doctors and consultation rooms may provide less flexibility in scheduling patient appointments and allocating resources and affect the quality of the consultation process in the clinics. Further consideration should be given to incorporating the effects on those factors in the simulation for a broader evaluation of the consultation process in hospital clinics. Second, the simulation did not consider the effects of the varying numbers of doctors on the ways doctors work. For example, as doctors become more utilized in the clinics, they may have less flexibility in scheduling their other work commitments and less time for other assignments such as research, meetings, and so on. These limitations are certainly not exhaustive, but important ones. Obviously, these limitations, in turn, suggest several possibilities for future study.

6 References

[1] Aharonson-Daniel L., Paul R.J. and Hedley A.J. (1996). “Management of queues in out-patient departments: the use of computer simulation”, Journal of Management in Medicine 10, 50-58.
[2] Agnihothri S.R. and Taylor P.F. (1991). “Staffing a centralized appointment scheduling department in Lourdes Hospital”, Interfaces 21, 1-11.
[3] Anderson J.G. (2002). “Preface: Special issue of simulation in health care management”, Health Care Management Science 5(2), 73.
[4] Anderson J.G., Harshbarger W., Weng H.C., Jay S.J. and Anderson M.M. (2002). “Modeling the costs and outcomes of cardiovascular surgery”, Health Care Management Science 5(2), 103-111.
[5] Arvy C. and Morin J. (1979). “Improving patient access and service in regional OB/GYN out-patient clinics”, Proceedings of the HIMSS 1997 Winter Simulation Conference, 7-9.
[6] Azaiez M.N. and Al-Sharif S.S. (2005). “A 0-1 goal programming model for nurse scheduling”, Computers and Operations Research 32, 491-507.
[7] Babes M. and Sarma G. (1991). “Outpatient queues at the Ibn-Rochd health center”, Journal of the Operational Research Society 42, 845-855.
[8] Bailey N.T.J. (1952). “A study of queues and appointment systems in hospital out-patient departments, with special reference to waiting times”, Journal Royal Statistical Society 42, 845-855.
[9] Bard J.F., Binici C. and deSilva A.H. (2003). “Staff scheduling at the United States postal service”, Computers and Operations Research 30, 745-771.
[10] Brahimi M. and Worthington D.J. (1991). “Queuing models for outpatient appointment systems: a case study”, Journal of the Operational Research Society 42, 733-746.
[11] Callahan N.M. and Redmon W.K. (1987). “Effects of problem-based scheduling on patient waiting and staff utilization of time in a pediatric clinic”, Journal of Applied Behavior Analysis 20(2), 193-199.
[12] Caprara A., Monaci M. and Toth P. (2003). “Models and algorithms for a staff scheduling problem”, Mathematical Programming 98, 445-476.

[13] Cheang B., Li H., Lim A. and Rodrigues B. (2003). "Nurse rostering problems- a bibliographic survey", European Journal of Operational Research 151, 447-460.
[14] De Vries T. and Beekman R.E. (1998). "Applying simple dynamic modeling for decision support in planning regional health care", European Journal of Operational Research 105, 277-284.
[15] Denton B., Viapiano J. and Vogl A. (2007). "Optimization of surgery sequencing and scheduling decisions under uncertainty", Healthcare Management Science 10(1), 13-24.
[16] Elveback L. and Varma A. (1965). "Simulation of mathematical models for public health problems", Public Health Reports 80(12), 1067-1076.
[17] Fei H., Combes C., Meskens N. and Chu C. (2006). "Endoscopies scheduling problem: a case study", Proceedings of INCOM, Saint Etienne, France, 1-6.
[18] Flagle C.D. (1970). "The role of simulation in health services", American Journal of Public Health 60(12), 2386-2394.
[19] Grumbach K., Keane D. and Bindman A. (1993). "Primary care and public emergency department overcrowding", American Journal of public Health 83(3), 372-378.
[20] Hariharan S., Chen D. and Merritt-Charles L. (2006). "Evaluation of the utilization of the preanaesthetic clinics in a university teaching hospital", BMC health Services Research 6, 59.
[21] Harper P.R. and Gamlin H.M. (2003). "Reduced outpatient waiting times with improved appointment scheduling: a simulation modeling approach", OR Spectrum 25, 207-222.
[22] Hearn C.R. and Bishop J.M. (1970). "Computer model simulating medical care in hospital", British Medical Journal 3(5719), 396-399.
[23] Hsieh P.J, Tan B. and Lin C. (2003). "An integrated approach to determine hospital outpatient staffing needs", International Journal of Healthcare Technology and Management 5, 96-122.
[24] Jacobson S.H. and Sewell E.C. (2002). "Using Monte Carlo simulation to determine combination vaccine price distributions for childhood diseases", Health Care Management Science 5(2), 135-145.
[25] Jeans W.D., Berger S.R and Gill R. (1972). "Computer simulation model of an X-ray department", British Medical Journal 1(5801), 675-679.
[26] Kelton D.W., Sadowski P.R. and Sadowski A.D. (1998). Simulation with Arena. WCB/McGraw-Hill, New York, USA.
[27] Kumar A. and Shim S.J. (2006). "Simulating staffing needs for surgical instrument distribution in hospitals", Journal of Medical Systems 30(5), 363-369.
[28] Lacy N.L., Paulman A. and Reuter M.D. (2004). "Why we don't come: patient perceptions on no-shows", Annals of Family Medicine 2(6), 541-545.
[29] Law A.M. and Kelton D.W. (2000). Simulation Modeling and Analysis. McGraw-Hill Higher Education, New York, USA.
[30] Lehaney B., Clarke S.A. and Paul R.J. (1999). "A case of an intervention in an outpatients department", Journal of the Operational Research Society 50, 877-891.
[31] Levy D.T., Chaloupka F., Gitchell J., Mendez D. and Warner K.E. (2002). "The use of simulation models for the surveillance, justification and understanding of tobacco control policies", Health Care Management Science 5(2), 113-120
[32] Lipscomb J., Kilpatrick K.E., Lee K.L. and Pieper K. (1995). "Determining VA physician requirements through empirically based models", Health Service Research 29(6), 697-717.
[33] Liyanage L. and Gale M. (1995). "Quality improvement for the Campbelltown hospital emergency service", 1995 IEEE International Conference on Systems, Man and Cybernetics. Intelligent Systems for the 21st Century 3, 1997-2002.
[34] Montgomery J.B., LaFrancois G.G. and Perry M.J. (2000). "Modeling access, cost, and perceived quality: computer simulation benefits orthodontic clinic staffing decisions", Military Medicine 165(2), 114-118.
[35] Naylor C.D., Levington C.M., Wheeler M. and Hunter L. Queuing for coronary surgery during severe supply-demand mismatch in a Canadian referral centre: A case study of implicit rationing Social Science & Medicine 37, 61-67.
[36] Parkerton P.H., Wagner E.H. and Smith D.G. (2003). "Effect of part-time practice on patient outcomes", Journal of General Internal Medicine 18(9), 717-724.
[37] Pritsker A.B., O'Reilly J.J. and LaVal O.K. (1997). Simulation with Visual SLAM and AWESIM. John Wiley & Sons, New York, USA.
[38] Proctor T. (1996). "Simulation in healthcare", Health Manpower Management 22(5), 40-44.
[39] Rauner M.S. (2002). "Using simulation for AIDS policy modeling: benefits for HIV/AIDS prevention policy makers in Vienna, Austria", Health Care Management Science 5(2), 121-134.
[40] Salma K. (2008). "Shorter wait to see SGH specialist", The Straits Times, Saturday, February 16, H3.
[41] Son Y.K. (1993). "Simulation-based manufacturing accounting for modern management", Journal of Manufacturing Systems 12(5), 417-427.

[42] Stepanovich P.L. and Uhrig J.D. (1999). "Decision making in high-velocity environments: implications for healthcare", Quality Management in Health Care 5(3), 72-79.
[43] Su S. and Shih C.L. (2002). "Managing a mixed-registration-type appointment system in outpatient clinic", International Journal of Medical Informatics 70, 31-40.
[44] Uyeno, D. (1974). "Health manpower systems: an application of simulation to the design of primary health care teams", Management Science 20, 981-989.
[45] Wang Q. (2004). "Modeling and analysis of high risk patient queues", European Journal of Operations Research 155, 502-515.
[46] Welch H.G., Chapko M.K., James K.E. and Schwartz L.M. (1999). "The role of patients and providers in the timing of follow-up visits", Journal of General Internal Medicine 14(4), 223-229.
[47] Wilt, A. and Goddin, D. (1989). "Health care case study: simulating staffing needs and work flow in an outpatient diagnostic center", Industrial Engineering 21(5), 22-29.
[48] Wijewickrama A.K.A. (2006). "Simulation analysis for reduced queues in mixed patients' outpatient department", International Journal of Simulation Modeling 5(2), 56-68.
[49] Zaric G.S. (2002). "Random vs. non-random mixing in network epidemic models", Health Care Management Science 5(2), 147-155.
[50] Zenios S.A. (1999). "Modeling the transplant waiting list: a queuing model with reneging" Queuing Systems 31, 239-251.