



Design and analysis of a health care clinic for homeless people using simulations

Health care clinic
for homeless
people

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Jared Reynolds

Manufacturing Center for Excellence, GE Aviation, Cincinnati, Ohio, USA

Zhen Zeng

Manufacturing Develop Program, Cummins Inc., Columbus, Indiana, USA

Jingshan Li

*Department of Electrical and Computer Engineering and
Center for Manufacturing, University of Kentucky, Lexington,
Kentucky, USA, and*

Shu-Yin Chiang

*Department of Information and Telecommunication Engineering,
Ming Chuan University, Taoyuan, Taiwan*

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Abstract

Purpose – Improving quality of care is important in health care management. For health care clinics, reducing patient waiting time and improving throughput with efficient utilization of the workforce are important issues to achieve better quality of care. This paper seeks to introduce a simulation study on design and analysis of a health clinic for homeless patients in Lexington, Kentucky, USA.

Design/methodology/approach – Using the simulation model, the patient flow of the clinic and analyze quality of care for different staffing levels is simulated. In addition, the dependence of distributions on service times is investigated. Moreover, the impact of service time variability on quality of care (e.g. patient waiting time) is analyzed.

Findings – The necessary staffing level and utilizations to reduce patient waiting times and improve throughput to achieve better quality of care are obtained. In addition, it is shown that the system performance is primarily dependent on the mean and coefficients of variation, rather than a complete distribution, of service times. In addition, a piece-wise linear approximation formula is proposed so that patient waiting time in the clinic can be estimated for any variability with only two simulations.

Research limitations/implications – The simulation method may need long model development time and long simulation executing time for complex systems.

Practical implications – The quality of care delivery in a health care clinic can be evaluated using simulations. The results presented in the paper provide an easier approach for medical practitioners to evaluate different scenarios, examine needed resources, and carry out what-if analysis to predict the impact of any changes in the system, to determine an optimal system configuration.

Originality/value – The paper shows that such models provide a quantitative tool for clinic operations and management to achieve better care quality. Moreover, it can be easily adapted to model other health care facilities, such as hospitals, emergency rooms, operating rooms, supply chain in health care industry.

Keywords Medical care, Health services, Quality, Homelessness, United States of America

Paper type Research paper



Introduction

A health clinic is planned to provide the basic health care free of charge for homeless people in Lexington, Kentucky, USA. This clinic is completely supported by charity groups and will be operated by volunteering staffs of nurses, doctors, pharmacists, etc., to offer health care needs and help increase the opportunities for the impoverished people. A successful establishment of the clinic will not only provide timely care to homeless patients, but also help reducing the overcrowding in emergency departments in local hospitals and other health care facilities. In order to achieve the best quality of care of the clinic, analyzing the patient outcome, in particular, patient waiting time and throughput, based on various staffing levels, is of importance.

To accomplish this, discrete event simulation models can be carried out to investigate various scenarios and their impacts on patient outcome and quality of care (Banks *et al.*, 2004). In recent years, due to the dramatic increase in health care cost, and development of user-friendly and more functional simulation software, more and more simulation studies have been applied to health care management as an effective decision-making tool (see Jacobson *et al.*, 2006) for an overview of simulation modeling applications to health care clinics and hospitals, etc., during the last forty years). Typically, such studies include patient flow analysis in clinics, emergency and operating rooms, scheduling outpatient visits and resources, capacity sizing and staff planning, etc. Using these models one can have a better understanding of the relationship between various variables in health care systems so that it could help minimizing cost and increasing quality of service (i.e. better patient satisfaction).

In this paper, a simulation model is developed with *Simul8* (Hauge and Paige, 2002) to analyze the patient flow in the clinic to achieve better quality of care. Since the clinic will be operated by volunteered staffs, focusing on the impacts to the patient outcome based on staffing levels would be most practical. Such models can provide a simple and quantitative tool for clinic management and health care staffs to provide care with better quality for impoverished community.

The remainder of the paper consists of the following sections: a brief review of the related literature; simulation model and analysis results; impacts of distribution types and variability of service times on system performance. Finally, the conclusions are provided.

Literature review

Using simulation to analyze health care systems can be traced back to 1960s and received continuous attention from both simulation and health care research communities. For example, as one of the earliest work, Fetter and Thompson (1965) study utilization rate of physicians for outpatient clinics. Rising *et al.* (1973) address patient scheduling issues to improve patient throughput and reduce clinic overtime. Facility dimensioning problem and the sizing of the assistance term for pediatric care are studied to determine optimal number of beds and choice of nurse duty by Romanin-Jacur and Facchin (1987). Kumar and Kapur (1989) describe using simulations for scheduling staff for emergency room. The issues of using fast tracks to reduce waiting times in emergency rooms are investigated by Blake *et al.* (1996). Klein *et al.* (1993) present a review on operational and medical decision making and system planning models in health care.

In recent years, a substantial increase of applications of simulations in health care systems has been observed. For instance, design and development of discrete-event

(visual) simulation models for physician clinic environment within a physician network are introduced by Swisher *et al.* (2001). Swisher and Jacobson (2002) introduce a methodology for determining appropriate staff and physical resources in a health clinic using simulation models. To provide better management of an elective surgery waiting system, Everett (2002) presents a decision support simulation to help match patient needs with hospital availability. Baesler *et al.* (2003) describe the study using simulations to estimate the maximum possible demand increment in an emergency room of a private hospital. A flexible platform to investigate emergency department operations using simulation, EDSIM, is introduced by Connelly and Bair (2004). Sinreich and Marmor (2005) discuss the basis for developing a simulation tool for emergency room operations. In addition, a simulation model is proposed by Tayfur and Taaffe (2007) to evaluate the hospital performance in case of an evacuation due to hurricanes.

In addition to simulation models, other alternatives analyzing clinic flow and operations have been carried out as well. Lynam *et al.* (1994) present client flow analysis (CFA) to address the causes of long patient waiting times. Such a method allows clinic managers and workers to look at the clients and patients move through the clinic to identify waiting times, bottleneck areas and services and staff utilization patterns. Khandelwal and Lynch (1999) introduce a reengineering of the patient flow process at the Western Sydney Area Health Service through business process reengineering (BPR). Such a process greatly enhances service to the patient and improves the relationship between patients and medical officers. Moreover, clinical process analysis and activity-based costing (ABC) management are carried out at a heart center in Sweden to administrate cost information, aid strategic decision-making and quality improvement and cost reduction activities (Ridderstolpe *et al.*, 2002). Kerr *et al.* (2002) describe redesigning cancer service to improve cancer care through collaborative cancer networks. More than 50 percent reduction in care delay has been obtained during the first year's experience. Siegel and Reiner (2002) use picture archiving and communication systems (PACS) to redesign workflow in radiology department. It has shown great benefit of the transition to a digital system both in the imaging department and throughout the health care enterprise. Baker (2006) claims that better reporting of quality improvement efforts could strengthen the contribution of quality improvement research to health care. A systematic review of application of statistical process control in health care improvement is introduced by Thor *et al.* (2007).

Simulation modeling and analysis

The objective of the health clinic introduced in this paper is to provide free health care to the impoverished community of Lexington, Kentucky. In this clinic, nurses and doctors will be there on their volunteered time helping to provide necessary health care for the patients. A host of volunteered receptionists will be available to meet the patients and perform various services. The receptionists will greet the patients as they enter the clinic and admit them for care. They are also available to discuss issues with the patients and help them where and when applicable. In addition, a pharmacy with the ability to provide the basic pharmaceutical needs of the patients is planned. A radiologist staff will have the capability to perform X-rays to injuries. Specifically, after reception, patients needing medical services are routed to one of the available

patient rooms. A nurse then a doctor will meet the patients to deliver the service. After diagnosis, the patients either leave the clinic; or are routed to pharmacy to take prescriptions; or to radiology if an additional test is necessary. Since the clinic only provides basic medical service, patients may take the radiology test results to the hospital for further examination. Some injury patients may need casting and pain relief prescriptions before leaving the clinic. In addition, some patients may not need to see the nurse or doctor by only taking non-prescriptive medicines in pharmacy directly (see Figure 1 for patient routing illustration).

Simul8 model

Based on extensive discussions with medical professionals, a simulation model is proposed to study the patient flow. The percentages of patients that will go to pharmacy, radiology, casting, etc., are presented in Figure 1.

In the simulation model, patients are treated as entities flowing in the system and the services are viewed as work centers. The doctors, nurses, and other staffs are modeled as resources. Using the survey data from population study, we assume 50 patients per day to visit the clinic (i.e. inter-arrival time $\lambda = 9.6$ minutes). Let N_d and N_n denote the number of doctors and nurses, respectively. The following performance measures are introduced to characterize the quality of care:

- TP = system throughput (patients/hour).
- e_d = utilization of doctors.
- e_n = utilization of nurses.
- e_{ph} = utilization of pharmacist.
- e_{rp} = utilization of receptionist.
- e_{xr} = utilization of radiologist.
- T_{wr} = average waiting time in waiting room (min).
- T_{ph} = average waiting time in pharmacy (min).
- T_{xr} = average waiting time in radiology (min).
- q_{wr} = waiting room average occupancy.
- q_{xr} = radiology average queue length.
- q_{ph} = pharmacy average queue length.

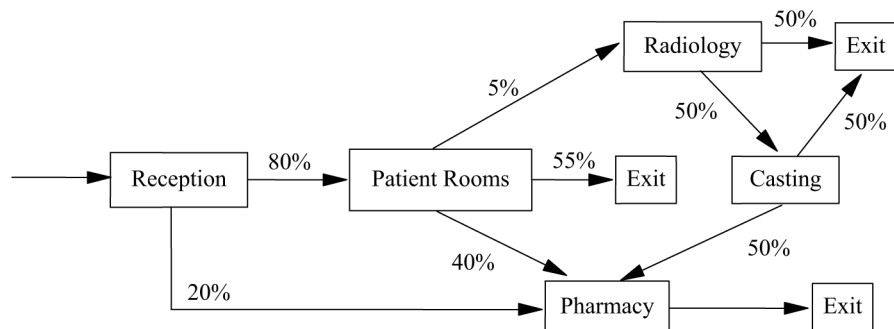


Figure 1.
Patient flow of the health clinic

By assuming different staffing levels, simulations are carried out to evaluate these performance indices. These simulations are set up as follows: in each simulation, 10,000 minutes of warm up time are assumed, and the next 100,000 minutes are used for collecting steady state statistics. A total of 20 replications are carried out to obtain the average performance (throughput, waiting time, utilization, etc.), with 95 percent confidence intervals consistently ranging less than 0.5 percent of their corresponding average values. Due to space limitation, only the average results are illustrated in the tables and figures in this paper. The results are summarized in Tables I to III (similar confidence interval levels are observed in all subsequent analysis).

By reviewing the results from the simulation, we conclude that:

- Except case 1 (one doctor, one nurse), all other combinations could achieve the desired throughput, i.e. are capable of serving the needs of this clinic.

	N_n	N_d	TP	q_{wr}	q_{ph}	q_{xr}
Case 1	1	1	4.75	24.99	0.02	0.02
Case 2	2	1	6.24	1.69	0.04	0.0
Case 3	3	1	6.24	1.50	0.04	0.0
Case 4	4	1	6.24	1.45	0.04	0.0
Case 5	2	2	6.24	0.39	0.05	0.0
Case 6	3	2	6.24	0.03	0.05	0.0
Case 7	4	2	6.24	0.0	0.05	0.0
Case 8	3	3	6.24	0.03	0.05	0.0

Table I.
Simulation results for 50 arrivals per day: throughput and average queue size

	N_n	N_d	T_{wr}	T_{ph}	T_{xr}
Case 1	1	1	394.83	0.50	5.27
Case 2	2	1	20.24	0.68	0.48
Case 3	3	1	17.99	0.69	0.18
Case 4	4	1	17.43	0.69	0.17
Case 5	2	2	4.69	0.84	0.95
Case 6	3	2	0.31	0.91	0.31
Case 7	4	2	0.02	0.91	0.27
Case 8	3	3	0.31	0.95	0.35

Table II.
Simulation results for 50 arrivals per day: average waiting time in the queue

	N_n	N_d	e_n	e_d	e_{rp}	e_{ph}	e_{xr}
Case 1	1	1	100	66.68	39.60	20.98	3.87
Case 2	2	1	65.68	87.59	51.96	27.54	5.08
Case 3	3	1	43.47	87.60	51.96	27.55	5.08
Case 4	4	1	32.31	87.60	51.96	27.55	5.08
Case 5	2	2	65.69	43.70	51.96	27.55	5.08
Case 6	3	2	6.24	43.70	51.96	27.55	5.08
Case 7	4	2	6.24	43.69	51.96	27.55	5.08
Case 8	3	3	6.24	28.75	51.96	27.55	5.08

Table III.
Simulation results for 50 arrivals per day: utilizations (%)

- Cases 2-4 result in close to 20 minutes waiting time. It is shown that increasing the number of nurses from two to four, the reduction in waiting time is not dramatic. Thus, the number of doctor (only one) is becoming the bottleneck in these cases.
- Case 5 increases the number of doctors to two. Even with only two nurses, the waiting time is dropping to less than 5 minutes.
- More nurses (cases 6 and 7) will result in almost no waiting at all.
- Similar results are observed for case 8 where both the numbers of doctors and nurses are selected as three.

Since the clinic is operated on volunteered times by the staffs, and doctor times are typically assumed to be more valuable (in terms of cost), it will be reasonable to assume that they are harder to serve in the clinic. In addition, there are less doctor resources around than nurses. Therefore, it might be preferable to use the configuration of case 2 (one doctor and two nurses) or case 3 (one doctor and three nurses). The deficiency here is that the patients need to wait for about 17 to 20 minutes in the waiting room. If lower waiting time is the major concern (given that the volunteer doctor is available), then the scenario of case 5 (two doctors and two nurses) would be a better choice.

To further study these configurations under different scenarios, sensitivity study is carried out next.

Sensitivity analysis

Pharmacist. Owing to the nature of the clinic for homeless people, a significant number of patients may select the pharmacy only option. Therefore, we double the service time of the pharmacist and increase the percentage of patients directly going to pharmacy to 30 percent (accordingly, the percentage of patients to see doctors and nurses is reduced to 70 percent). The results of this change are shown in Table IV. It can be seen that the biggest impact on the system performance is that the pharmacy queue waiting time increases from essentially less than one to seven minutes. The patients waiting time in the waiting room is also reduced since less patients need to see the doctors. The impacts on other performance indices are minimal. Therefore, in either case, having only one pharmacist is adequate to fulfill the demand in a reasonable time.

Increased patient arrivals. For the future, as the clinic matures or in the case of infection season that more patients come to the clinic per day, it is desirable to determine the appropriate staffing levels so that better quality of care can still be achieved. Table V presents the results in the scenario of 100 patients per day visiting the clinic.

As the number of patients doubled while the amount of time to complete the work remains the same, it is intuitive that more staffing will be required. According to Table V, it is shown that the best configuration of doctors and nurses to meet system

Table IV.
Simulation results for
increased pharmacy
workload

N_n	N_d	TP	T_{wr}	q_{wr}	T_{ph}	q_{ph}
2	1	6.2	20.26	1.47	6.52	0.40
3	1	6.2	9.04	0.65	6.69	0.40
2	2	6.2	3.08	0.22	7.21	0.44

throughput with reasonable queuing times and waiting room occupancies is a staffing level of four nurses and two doctors. Again, the utilization of pharmacist (and radiologist) is still low, and only one would be required.

Effects of service time distributions

Simulation needs to assume a certain type of distribution for service times. However, in practice, it is unlikely these times will follow exactly a designed distribution and it is typically impossible to discover the type of distributions of them. Even if the simulation model can directly load these data and distributions can be estimated through data fitting, analyses need to be repeated even with minimal changes. Therefore, a sensitivity study to investigate the dependence of the results on the type of the distribution is important. If it is the case that the results are independent of the distribution type, but only dependent on the moments, then it makes the work much easier since we can use practically any type of distribution with the same moments to obtain the required results. In other words, quality of care can be ensured no matter which distribution we assumed in the model.

To investigate this issue, normal, Weibull, Erlang, and log-normal distributions are considered in this study. The reason to select these distributions is that they have two parameters which enable us to assign mean and coefficient of variations (CV) with more freedom. Among all the distributions, same mean and coefficient of variations are assumed. Moreover, two additional cases with mixed distributions are generated, where for each one (reception, nurse, doctor, radiology, casting, pharmacy), a distribution is randomly selected equiprobably from the set (normal, log-normal, Weibull, Erlang). As an example, the following two cases, mix 1 and mix 2, are illustrated in Table VI.

Analysis with one doctor

First, we consider the case that there is only one doctor serving in the clinic. The simulation results are illustrated in Figure 2.

It is clear from these results that as long as the mean and coefficient of variation are held constant, the results are practically independent of distribution type. A paired *t*

N_n	N_d	TP	T_{wr}	q_{wr}	T_{ph}	q_{ph}
1	1	4.64	408.82	24.95	0.02	0.45
2	1	6.61	281.05	24.86	0.04	0.74
3	1	7.06	262.81	24.78	0.05	0.84
2	2	9.26	198.06	24.48	0.11	1.41
3	2	11.98	35.20	5.63	2.19	0.23
4	2	12	2.73	0.44	2.21	0.23
3	3	12	2.85	0.46	2.27	0.24

Table V.
Simulation results for 100
patients per day

	Reception	Nurse	Doctor	Radiology	Casting	Pharmacy
Mix 1	Normal	Log-normal	Weibull	Erlang	Log-normal	Erlang
Mix 2	Weibull	Erlang	Log-normal	Normal	Erlang	Log-normal

Table VI.
Mixed cases

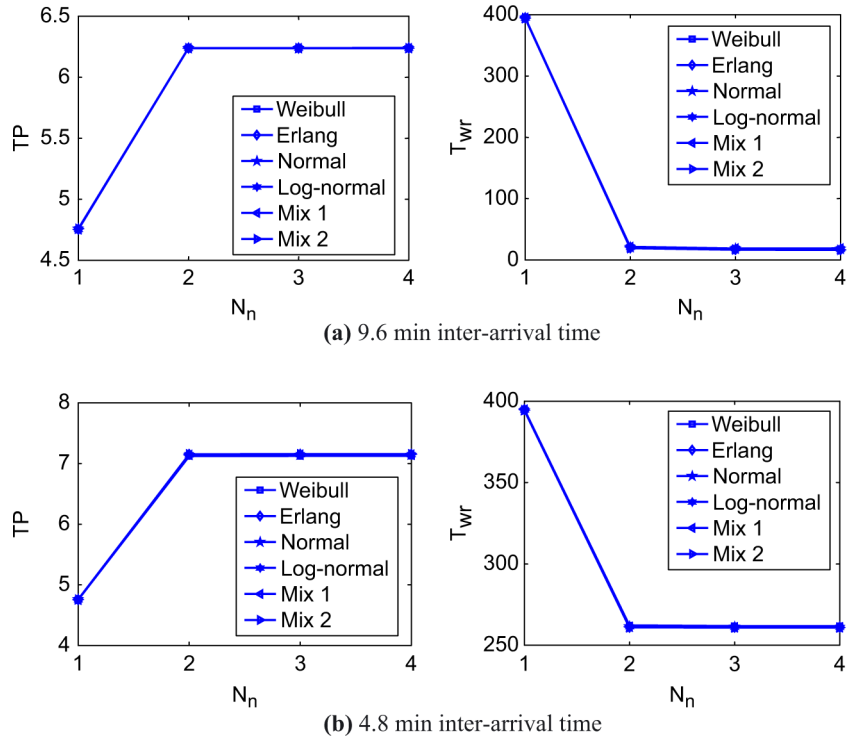


Figure 2.
Effects of service time distributions in the scenario of one doctor

test has been carried out to compare any of two data series with different distributions. We obtain p values consistently greater than 0.05 (for example, p values range from 0.2 to 0.5 for 9.6 min inter-arrival time case), which implies the differences between any two data series are practically insignificant. Similar results on all p values in subsequent analysis are observed.

To further examine the distribution dependency, data sets with randomly generated mean and CV for service times are used to analyze the system. The results of two of these data sets (denoted as RND 1 and RND 2) are shown in Figure 3. Again it validates the conclusions we obtained before, i.e. the performance is practically independent of distribution types.

Analysis with two doctors

To evaluate the case with additional resources, the scenarios of two doctors are analyzed (Figure 4). The results obtained follow the same trends found with one doctor case.

In addition, we evaluate the scenario with randomly generated data sets RND 1 and RND 2 again, and the results are summarized in Figure 5.

As one can be see, adding more doctors into the system, while maintaining the same mean and coefficient of variation, will not cause the qualitative results to change. This

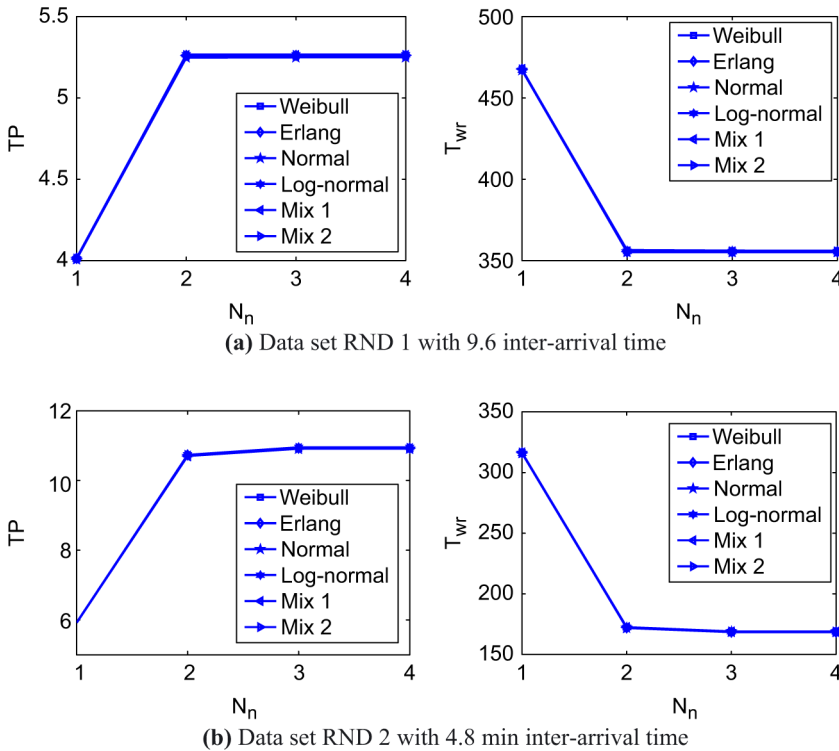


Figure 3.
Effects of distribution
types in the scenario of one
doctor with random data
sets

again confirms that the results are independent of distribution type. Therefore, we propose the following hypothesis:

- H1.* For a health care clinic described in this paper, the quality of care (throughput, average waiting time, etc.) is practically independent of the distribution types of the service times, but primarily dependent on the mean and coefficients of variations. In other words, given the mean and coefficient of variations, we can select any unimodal distribution type for simulation.

Effects of service time variability

Intuitively we expect that the system performance is degrading with respect to variability of the service times. To illustrate this, we evaluate the patient average waiting time in the waiting room under different coefficients of variation of service times, where all service time $CV = 0.1, 0.25, 0.5, 0.75, 0.9$, respectively. It is shown that the patient waiting time is in general an increasing function of service time coefficients of variations. The results are shown in Figure 6 as the solid lines for the cases of one or two doctors and two or three nurses.

Simulation results reported above provide a characterization of patient waiting time for $CV = 0.1, 0.25, 0.5, 0.75$, and 0.9 . However, for other CV s, additional simulations are

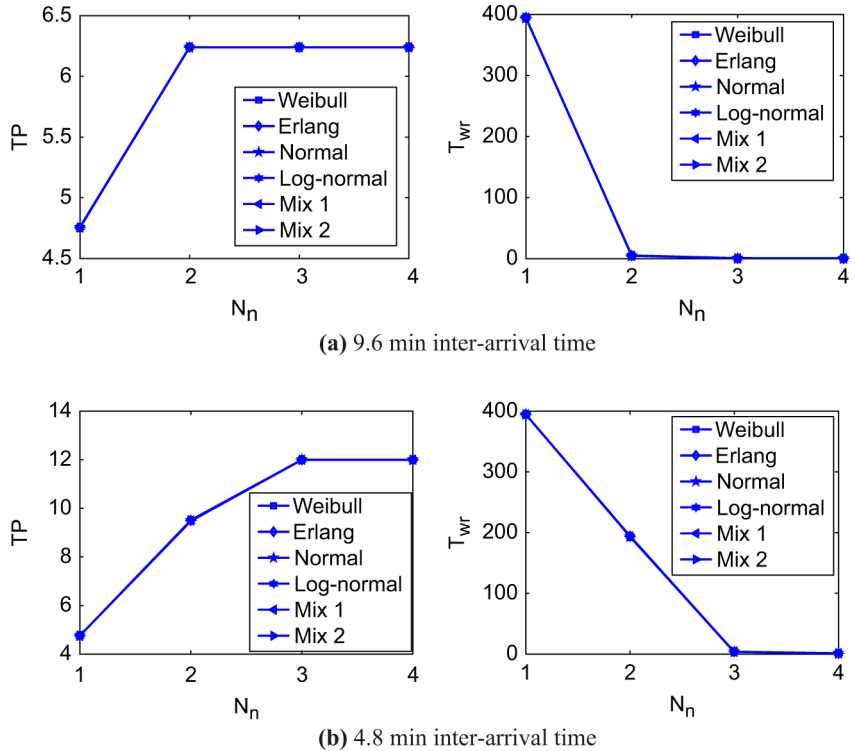


Figure 4.
Effects of service time distributions in the scenario of two doctors

needed. Therefore, an approximation method to evaluate T_{wr} is desirable. Although an exact characterization may not be possible, discovering an upper bound is feasible. Considering that the changes in T_{wr} is relatively slow when $CV \leq 0.5$, and fast when $1 > CV > 0.5$, we introduce an upper bound by a piece-wise linear function. Let $T_{wr}(CV)$ denote the patient waiting time for a given CV . When $T_{wr}(CV)$ for $CV = 0.5$ and $CV = CV_{max} \leq 1$ (in this paper, $CV_{max} = 0.9$) are given, the upper bound $T_{wr}^{upper}(CV)$ for any CV can be expressed by:

$$T_{wr}^{upper}(CV) = \begin{cases} T_{wr}(0.5), & CV \leq 0.5 \\ T_{wr}(0.5) + \frac{CV-0.5}{CV_{max}-0.5}(T_{wr}(CV_{max}) - T_{wr}(0.5)), & 0.5 < CV \leq CV_{max} \leq 1. \end{cases} \quad (1)$$

Such bounds are illustrated as dash lines in Figure 6. Therefore, with knowing only two points, $T_{wr}(CV_{max})$ and $T_{wr}(0.5)$, for any CV , without running additional simulations, the average patient waiting time can be approximated and will satisfy:

$$T_{wr}(CV) \leq T_{wr}^{upper}(CV). \quad (2)$$

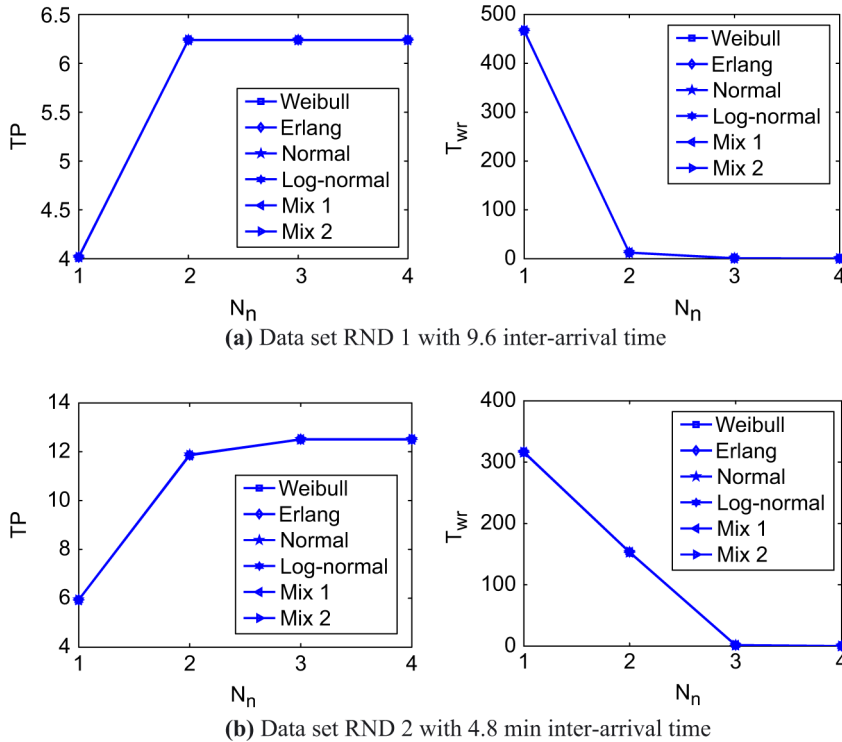


Figure 5.
Effects of distribution
types in the scenario of
two doctors with random
data sets

Note that although a polynomial approximation, e.g. quadratic function, may be possible to characterize the curves in Figure 6, it will need more information and may be parameter dependent. Therefore, equation (1) provides a more simple approximation without losing too much accuracy.

Additional results are obtained for more examples of 4.8 min. inter-arrival time of the patients, and random data sets RND 1 and RND 2, and are illustrated in Figure 7. These results again indicate that patient waiting time increases with more variability and expressions (1) and (2) can be used as empirical formulas for patient waiting time evaluation (except a few cases where little and neglectable discrepancies may be found when CV is small due to simulation accuracies).

Also note that a simpler linear approximation:

$$T_{wr}^{upper}(CV) = T_{wr}(CV_{min}) + \frac{CV - CV_{min}}{CV_{max} - CV_{min}} (T_{wr}(CV_{max}) - T_{wr}(CV_{min})),$$

can be used as another upper bound, for a given CV_{min} and CV_{max} . Again, only two simulations at CV_{min} and CV_{max} are need for such an approximation. Numerical experiments show that in most cases, the accuracy of this approximation is inferior to that of (1).

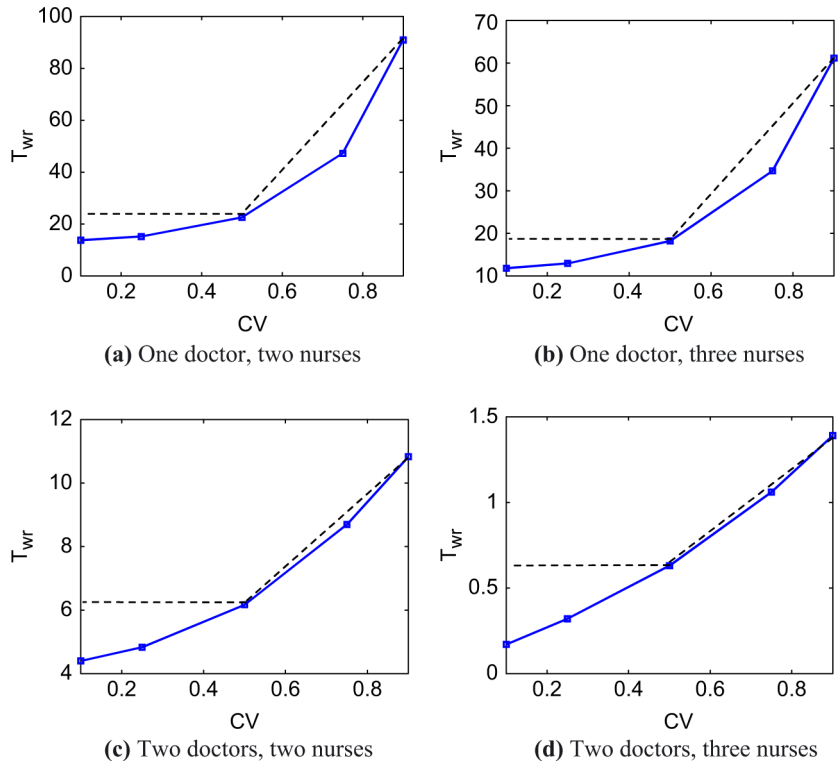


Figure 6.
Effects of service time
variability: 9.6 min patient
inter-arrival time

Conclusions

In this paper, we introduce a simulation study to design and analyze a health care clinic for homeless patients in Lexington, Kentucky. Using this model, we simulate the patient flow of the clinic and evaluate the quality of care (in terms of patient average waiting times and throughput) to determine an appropriate staffing level. In addition, we investigate the sensitivity with respect to service time distributions, and it is shown that the system performance is practically only dependent on the mean and coefficients of variation, rather than a complete distribution, of the service times. This enables us that selecting any type of distributions at hand for simulation we will obtain the same level of care quality. Moreover, we illustrate that the patient waiting time will increase as a function of service time variability. A piece-wise linear function is proposed as the upper bound of these waiting times so that they can be approximated for any coefficients of variation with the knowledge of two simulations only.

Such models provide a quantitative tool for clinic operations and management to achieve better care quality. Using such a tool, medical practitioners can evaluate different scenarios, examine needed resources, and carry out what-if analysis to predict the impact of any changes in the system, to determine an optimal system configuration. The results on insensitivity to distribution types and linear piece-wise function provide an easier approach for analysis, which significantly reduces the workload of simulations. Moreover, it can be easily adapted to model other health care facilities to

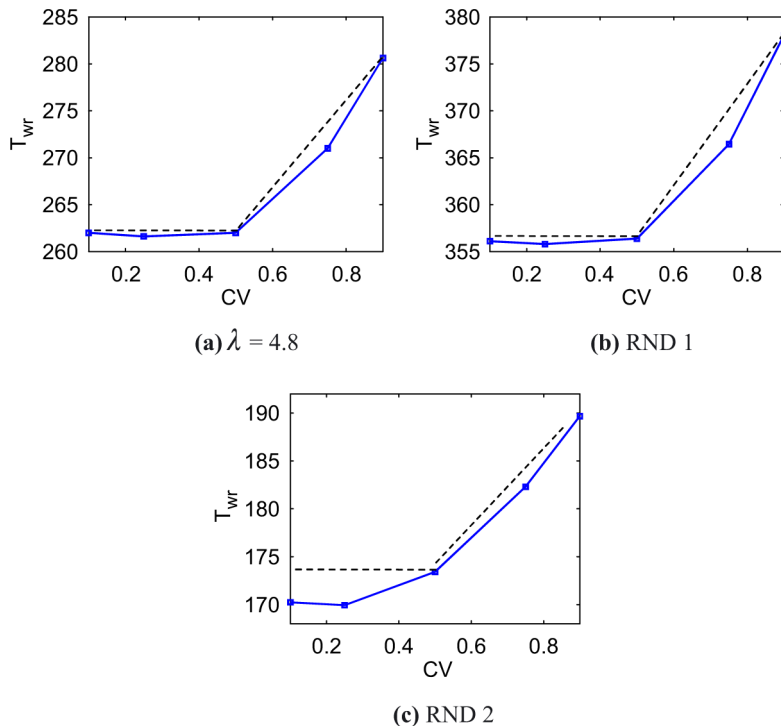


Figure 7.
Effects of service time
variability: additional
examples

accommodate their needs. The future work can also be directed to develop analytical method described by stochastic equations for performance evaluation and continuous improvement of clinics and other health care units, so that clinic performance can be analyzed quickly and system theoretic properties can be investigated.

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Corresponding author

Jingshan Li can be contacted at: jingshan@engr.uky.edu

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