TECHNICAL RESEARCH REPORT

Comparing Queueing Software for Mass Dispensing and Vaccination Clinics

by Mark Treadwell, Jeffrey W. Herrmann

TR 2005-113

INSTITUTE FOR SYSTEMS RESEARCH

ISR develops, applies and teaches advanced methodologies of design and analysis to solve complex, hierarchical, heterogeneous and dynamic problems of engineering technology and systems for industry and government.

ISR is a permanent institute of the University of Maryland, within the Glenn L. Martin Institute of Technology/A. James Clark School of Engineering. It is a National Science Foundation Engineering Research Center.

Web site http://www.isr.umd.edu

COMPARING QUEUEING SOFTWARE FOR MASS DISPENSING AND VACCINATION CLINICS

Mark A. Treadwell
Jeffrey W. Herrmann

Institute for Systems Research
University of Maryland
College Park, MD 20742

ABSTRACT

Simulation models have been developed for use in evaluating the performance of mass vaccination clinics; spreadsheet forms of these models have also been produced for the benefit of end-users without access to simulation software. The same clinics are modeled in several queueing software packages, and the performance of the models is compared.

1 INTRODUCTION

In 2004 Public Health Services of the Montgomery County, Maryland Department of Health and Human Services (DHHS) became one of the first eleven public health agencies in the nation to be recognized as Public Health Ready by the National Association of County and City Health Officials (NACCHO) and the Centers for Disease Control and Prevention (CDC) of the U.S. Department of Health and Human Services. The county is home to one of eight Advanced Practice Centers (APCs) for Public Health Preparedness funded by NACCHO through the CDC. Montgomery County DHHS has been tasked with developing tools to track the spread of communicable disease and create models of treatment dispensing clinics. In 2004 and 2005, simulation models were developed to accurately model patient flow through clinics. Customizable spreadsheet models were also created using queueing theory, providing equivalent functionality for users without access to a sophisticated simulation package.

2 METHODOLOGY

In order to validate the spreadsheet modeling tool, two queueing software packages were obtained. These packages were Rapid Analysis of Queueing Systems (RAQS), a Windows application developed at Oklahoma State's Center for Computer Integrated Manufacturing (Kamath et al, 1995), and Queueing Theory Software Plus (QTS-Plus), an Excel-based package authored by James Thompson, Carl Harris, and Donald Gross. RAQS uses the parametric decomposition approach to solving queueing networks (Segal and Whitt, 1989 and Whitt, 1983), while QTS-Plus is based around equations from Gross and Harris (1974). Models were also produced with CIM Lab's Clinic Planning Model Generator. This Excel-based tool was developed to help public health officials plan clinics that have sufficient capacity to serve residents quickly while avoiding unnecessary congestion.

Models of two different clinics were developed in each of the four packages. Model A (see Table 2 below) is based on a time study of a clinic exercise performed in April of 2005. Model B (see Table 2 below) represents a fictitious but realistic clinic. The routing matrices for the two models are given in Table 3 and Table 4 below. The arrival SCV at the first station equals one in both models. No batching occurs in either model. (This was necessary because the RAQS and QTS Plus software cannot model queueing networks with process batches.)

In RAQS and QTSPlus, each clinic was modeled using an open Jackson queueing network with these parameters. Discrete event simulation models of the two clinics were also created using Rockwell Software's Arena® 5.00. Both models were run with 100 replications of 800 hours, with 4 hours of warm-up time allowed to achieve steady state.

Table 1: Parameters for Model A.

Node	Number of Servers	Service Time (min)	Service Time SCV
1	5	1.237	0.725
2	8	0.585	0.687
3	8	1.34	0.301
4	8	1.154	0.4
5	2	1.304	0.296
6	10	1.752	0.524
7	8	3.765	0.558
8	8	1.051	0.297
9	4	12.698	0.467
10	1	10	0

Table 2: Parameters for Model B.

Node	Number of Servers	Service Time (min)	Service Time SCV
1	2	0.259	1.105
2	2	1.752	0.525
3	6	1.154	0.4
4	9	1.752	0.525
5	3	3.765	0.308
6	7	1.34	0.301
7	5	12.698	0.467

Table 3: Routing Table for Model A

	To									
From	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Exit**
1	0.76	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2		0.42	0.39	0.10	0.03	0.00	0.04	0.01	0.00	0.01
3			0.10	0.07	0.01	0.01	0.03	0.00	0.00	0.77
4				0.49	0.31	0.04	0.13	0.01	0.00	0.01
5					0.25	0.07	0.59	0.05	0.00	0.04
6						0.38	0.52	0.05	0.00	0.05
7							0.78	0.08	0.00	0.14
8								0.00	0.01	0.99
9									0.09	0.91
10										1.00

Table 4: Routing Table for Model B

	To					
From	**2**	**3**	**4**	**5**	**6**	**7**	**Exit**
1	0.10	0.90	0.00	0.00	0.00	0.00	0.00
2		0.50	0.00	0.00	0.00	0.50	0.00
3			1.00	0.00	0.00	0.00	0.00
4				0.10	0.90	0.00	0.00
5					0.50	0.00	0.50
6						0.00	1.00
7							1.00

Both clinics were tested at several levels of patient arrival, corresponding to 50%, 80%, 90%, 95%, and 99% of clinic capacity; Models A and B have capacities of 4.043 and 5.407 patients/minute, respectively. Data was recorded for mean total time and mean queueing time at each node, as well as mean time in system and mean system WIP. Data from the simulation model of the clinic was taken as the baseline set. The differences between each model and the baseline set was calculated, and compared with the width of the 95% confidence interval on the simulation data.

3 RESULTS

3.1 Model A Results

In Model A, deviations from the simulation model in average total time and average total WIP had the values given in Table 5 below. Through every station of the clinic and in the total time in system, the RAQS model matched the simulation most closely, although it was still significantly outside the 95% confidence interval of the simulation results. In total WIP, the spreadsheet model provides a better approximation than RAQS for the three scenarios with higher utilization, and even approaches the limits of the 95% confidence interval.

Because the queueing times at most stations were so small, tiny differences were greatly exaggerated in the calculation of results; only stations with longer queueing times will be examined here. Two stations in this model have queueing times over one minute at any of the five operating levels: Reception and Education. At Reception, all three models are fairly consistent; at Education, the spreadsheet model and the RAQS model are very close to simulation values, though the deviation in the QTS-Plus model is much greater. This data is shown in the last two columns of Table 5.

Table 5: Average differences across scenarios (in minutes) in Model A

	Avg. Total Time	Avg. Total WIP	Reception Queue	Education Queue
Spreadsheet model	2.1454	2.6250	0.2817	0.0201
RAQS	1.0178	3.7260	0.3946	0.1896
QTS-Plus	2.8112	10.6093	0.9206	2.4208
Simulation 95% C.I.	0.2955	1.1874	0.2764	0.1705

3.2 Model B Results

In Model B, error in the average total time and average total WIP had the values given in Table 6 below, along with the average error in queueing times throughout the model. In the clinic total statistics, the RAQS model matched the simulation most closely, although the spreadsheet model was also well within the 95% confidence interval of the simulation results. For individual stations, the RAQS model was the only one within the 95% confidence interval of the simulation data, but the spreadsheet model was not far off. The estimates of the QTS-Plus model were consistently the least accurate. All of the models become more accurate at higher levels of utilization.

Table 6: Average differences across scenarios (in minutes) in Model B

	Avg. Total Time	Avg. Total WIP	Queueing Times (Avg.)
Spreadsheet model	0.1226	0.5900	0.0512
RAQS	0.0730	0.3386	0.0153
QTS-Plus	2.5097	13.1040	0.4780
95% C.I.	0.2146	1.1576	0.0396

4 CONCLUSIONS

Generally speaking, it appears that the models built using RAQS provide a better approximation of the simulation models than the spreadsheet models or the QTS-Plus models. However, the inaccuracies of all three models appear the greatest in situations where queueing times are significantly below one second. For the stations with longer queueing times, the approximations provided by the three models are much closer to the simulation model. Given that the RAQS models consistently give the closest estimates of the simulation models, their governing equations should be examined to determine how they differ from those used in the spreadsheet models, and whether they should be substituted into the spreadsheet models.

APPENDIX. THE CLINIC QUEUEING NETWORK MODEL

The analysis of queueing networks is a well-known problem, and different approximations for the general case have been presented. The following model is based on relationships that were independently derived, along with those provided by Hopp and Spearman (2001) and Buzacott and Shanthikumar (1993). "i" is used throughout to denote a station, with 0 referring to the bus arrival process and 1 through "I" referring to the stations in the clinic.

Inputs

P = Size of population to be treated
L = Time allotted for treatment
h = Daily hours of operation
N = Number of clinics
m_i = Number of staff at station i
c^2_{a1} = Arrival SCV at the first station.

Parameters

t_i= Process time at station i
σ^2_i = Process time variance at station i
v = Average walking speed
P_{ij} = Routing probability from station i to station j

Intermediate terms

r_i = Arrival rate at station i
c^2_{ai} = Arrival SCV at station i
c^2_{ei} = Process time SCV at station i
c^2_{di} = Departure SCV at station i
u_i = Utilization at station i
w_i = Wait time at station i

Outputs

TH' = Required throughput
CT_i = Cycle time at station i
CT = Time in clinic
WIP = Average number of patients in clinic
Q_i = Average queue length at station i

The throughput required to treat the population in the given time is $TH' = \frac{P}{L \cdot h \cdot N}$.

Arrival rates for the clinic and for individual stations are calculated based on the population and length of treatment:

$$r_i = \begin{cases} \dfrac{P}{L \cdot h \cdot N \cdot 60} & i = 1 \\ \sum_{j=1}^{i-1} r_j P_{ji} & i > 1 \end{cases}$$

Given staffing levels m_i are used to calculate station utilization: $u_i = \frac{r_i \cdot t_i}{m_i}$.

For each station, the SCV of arrivals, processes, and departures must be calculated:

$$c_{ai}^2 = \sum_{j=1}^{i-1} \left(\left(c_{di}^2 - 1 \right) \cdot P_{ji} + 1 \right) \cdot \frac{r_j \cdot P_{ji}}{r_i}$$

$$c_{ei}^2 = \frac{\sigma_i^2}{t_{ei}^2}$$

$$c_{di}^2 = 1 + \left(1 - u_i^2\right)\left(c_{ai}^2 - 1\right) + \frac{u_i^2}{\sqrt{m_i}}\left(c_{ei}^2 - 1\right)$$

The cycle time for each station is given by $CT_i = w_i + t_i$ where

$$w_i = \left(\frac{c_{ai}^2 + c_{ei}^2}{2}\right)\left(\frac{u_i^{\sqrt{2m_i+2}-1}}{m_i\left(1-u_i\right)}\right)t_i$$

The cycle time is then weighted based on the ratio of patient flow at a station to total patient flow and summed for an average total time in clinic.

$$CT_i' = CT_i \cdot \frac{r_i}{r_1}$$

$$CT = \sum_{i=1}^{I} CT_i'$$

Other statistics calculated include the average queue length at each station and the average total clinic WIP:

$$Q_i = w_i r_i$$

$$WIP = r_1 \cdot CT$$

REFERENCES

Gross, Donald and Carl Harris. 1974. Fundamentals of Queueing Theory. John Wiley and Sons, New York.

Kamath, M., S. Sivaramakrishnan, and G. Shirhatti. 1995. “RAQS: A software package to support instruction and research in queueing systems,” 4th Industrial Engineering Research Conference Proceedings, pp. 944-953, IIE, Norcross, GA.

Segal, M. and W. Whitt. 1989. A queueing network analyzer for manufacturing. Proceedings of the 12th International Teletraffic Congress, Torino, Italy, June 1988, 1146-1152.

Whitt, W. 1983. The queueing network analyzer. Bell Systems Technical J. 62 2779-2815.

ACKNOWLEDGMENTS

The authors wish to thank the staff of Montgomery County (Maryland) Public Health Services for their support, particularly Kay Aaby and Rachel Abbey.

This publication was supported by Cooperative Agreement Number U50/CCU302718 from the CDC to NACCHO. Its contents are solely the responsibility of the University of Maryland and the Advanced Practice Center for Public Health Emergency Preparedness and Response of Montgomery County, Maryland, and do not necessarily represent the official views of CDC or NACCHO.

AUTHOR BIOGRAPHIES

MARK A. TREADWELL is a Master’s student in the Department of Mechanical Engineering at the University of Maryland, College Park. He is a member of INFORMS and ASME. His e-mail address is <mtread@umd.edu>.

JEFFREY W. HERRMANN is an associate professor at the University of Maryland, College Park, where he holds a joint appointment with the Department of Mechanical Engineering and the Institute for Systems Research. He is the director of the Computer Integrated Manufacturing Laboratory. He is a member of INFORMS, ASME, IIE, SME, and ASEE. He received his Ph.D. in industrial and systems engineering from the University of Florida. His e-mail address is <jwh2@umd.edu>.