The Clinic Surge Planning Model: Performance Estimates and Validation Results

Adam Montjoy

Contents

Abstract

In case of a terrorist attack or natural outbreak of a contagious disease, it may be necessary to vaccinate patients in mass quantities. This paper focuses on the creation and implementation of a mathematical model that gives an estimate of the performance of a clinic with a modeled number of stations and staffing, given that there is a large number of patients waiting before the clinic opens. The model was created in Microsoft Excel so that it can be easily accessed by any clinic. Simulation for the purpose of validation was done in Rockwell Arena. Two separate simulations with different cases were compared to estimates made by the planning model to determine its accuracy.

1 Introduction

The Clinic Surge Planning Model (CSPM) is different from other clinic models in that it compensates for an initial group of patients, or a 'surge,' waiting before the clinic has opened. This model does not have a set number of hours; instead it has a period in which the clinic is still accepting patients. This model serves to show performance of the surge situation according to how many workers are present and individual station performance. This particular model runs in Microsoft Excel so that it can be easily used and operated by any clinic planner. To aid in this process, an additional user's guide has been prepared to show detailed information on operating the model. The purpose of this report is to describe the mathematical calculations in the model and show simulations that validate its operation.

2 Problem Setting

In general, the Clinic Surge Planning Model can be used to plan any clinic as long as it is run in a small period of time to vaccinate a large number of patients. This would make it useful in vaccinating a large population for a flu season. Primarily, this research is conducted for an emergency situation, such as anthrax or smallpox being introduced into a population as a bioterrorist act. In this situation, a large number of patients would need to be vaccinated quickly. A planning model would be needed to determine clinic performance and how many staff members to assign to each station.

3 Related Work on Clinic Planning

Recent events have sparked much work in clinic planning. Aside from other vaccination research done by University of Maryland's Institute for Systems Research, there has been other programs devoted to similar work. The Agency for Healthcare Research and Quality (AHRQ) funded research by the Weill Medical

College of Cornell University to develop the Bioterrorism and Epidemic Outbreak Response Model (BERM). The BERM predicts the number and type of staff that would be needed in case of a major disease outbreak or bioterrorism attack [3]. Also, the Center for Disease Control and Prevention has developed the Maxi-Vac model that can be used by local and state officials to plan large-scale smallpox vaccination clinics for large populations [2].

4 Mathematics of This Model

The calculations made in the CSPM are based on the conveyor model because the time in the clinic is determined by how much time is spent at each station, unless the clinic is full and waiting will occur for the patients. This being said, these 'conveyor-type,' calculations are most accurate when there is a highly constant amount of patients being serviced [6].

4.1 Demand Inputs

There are several demands for this model. They are as follows:

Number of patients initially waiting (P_0) - This is the surge.

Total number of patients (P_t) - This is the estimated patients the clinic plans to treat in the operating day including the initial number of patients waiting.

Time accepting new patients (T^*) - This is the scheduled time, in hours, in which the clinic is accepting patients. After this time the clinic will still be open, but only to finish servicing the patients already in the clinic.

Set of stations that are not self-service (S) - These are the stations that have one or more staff members. This set is used in calculating the service rate of the entire clinic.

Sequence of stations ($\{1, ..., n\}$) - This is the order in which the stations are set in the clinic. It is not possible for patients to go from a higher-numbered station to a lower-numbered one. The exit station is numbered $n + 1$.

Routing probabilities (P_{ij}) - Each P_{ij} equals the probability that a patient will enter station j given they are already leaving station i. There are several constraints for the probabilities. This model assumes that all patients are processed in the first station. Negative flows are not possible in this model. Also, no patient will leave a station and return to the same station. The following is true: $P_{ij} = 0 \ \forall j \leq i$, $P_{ij} \geq 0 \ \forall j > i$, $\sum_{j=i+1}^{n+1} P_{ij} = 1$.

Distance table (D_{ij}) - Each D_{ij} equals the distance to travel from station i to station j (in feet).

Processing Time (t_{ei}) - This is the average amount of time it takes to service one patient at station i, in minutes.

Staff (f_i) - This is the number of personnel working at station i $\forall i \in S$.

Batch size (k_i) - This is the number of patients that can be served by one staff member. $k_i = 0$ for self-service stations. $k_i \geq 1$ for $i \in S$.

4.2 Calculated Parameters

Relative arrival rate (λ_j) - $\lambda_1 = 1$. For $j = 2, ..., n$, λ_j is calculated as follows:

$$\lambda_j = \sum_{i<j} \lambda_i P_{ij}$$

Where j is the entering station, i would be all the stations leading into j, and P_{ij} is the probability that a patient enters station j given that they are at i.

Weighted walking time (t_{wi}) - This is the average time it takes for patients to walk between stations when leaving station i, in minutes. This is calculated as follows:

$$t_{wi} = \sum_{j>i} \frac{P_{ij} D_{ij}}{W}$$

Where D_{ij} is the distance, in feet, from station i to j and W is the average walking speed in feet per second.

Rate of arrival (r_a) - This is the rate in which patients are arriving while the clinic is still accepting patients. This is calculated, in patients per hour, as follows:

$$r_a = \frac{P_t - P_0}{T^*}$$

Raw process time (B) - This is the estimated time that it would take a patient to go through the clinic assuming there is no wait. This is calculated, in hours, as follows:

$$B = \tfrac{1}{60} \sum_{i=1}^{n} \lambda_i (t_{ei} + t_{wi})$$

Service rate (r_e) - This is the rate in which the clinic can serve the demand. This is calculated, in patients per hour, as follows:

$$r_e = \min_{i \in S} \{\frac{f_i r_{ei}}{\lambda_i}\}$$

Where r_{ei} is the service rate per staff at each individual station. This is calculated, in patients per hour, as follows:

$$r_{ei} = \frac{k_i}{t_{ei}}$$

4.3 Functions

The following functions are derived from the inputs:

Cumulative arrival function ($A(t)$) - This function is piecewise and is calculated as follows:

$$A(t) = \begin{cases} r_a t + P_0, & 0 \leq t \leq T^* \\ P_t, & \mathrm{T}^* \leq t \leq T_c \end{cases}$$

Actual service rate function ($S(t)$) - This function is also piecewise depending on whether the calculated service rate, r_e, is high enough to intersect the cumulative arrival rate before the clinic stops accepting patients. If the service rate is high enough to intersect the cumulative arrival rate ($T^* r_e \geq P_t$), then it is calculated as follows:

$$S(t) = \begin{cases} r_e t, & 0 \leq t \leq T_m \\ A(t), & \mathrm{T}_m \leq t \leq T_c \end{cases}$$

Where T_m is the point of intersection. This is found by the following:

$$T_m = \frac{P_0}{r_e - r_a}, \text{ assuming } r_e > r_a$$

If the service rate is not high enough to meet the cumulative arrival rate before the clinic stops accepting patients, then $S(t) = r_e t$ while $r_e t \leq P_t$.

Departure function ($D(t)$) - This function calculates the rate in which patients leave the clinic. It is calculated as follows:

$$D(t) = \begin{cases} 0, & 0 \leq t \leq B \\ S(t - B), & \mathrm{B} \leq t \leq T_c \end{cases}$$

4.4 Clinic Performance

With the given and imputed parameters, the clinic performance can be calculated. This involves the following:

Time clinic is open in hours (T_c) - If the service rate is high enough to meet the cumulative arrival rate of patients before the clinic stops accepting patients ($T^* r_e \geq P_t$), this value will be the time the clinic stops accepting patients plus the raw processing time. If this service rate is not high enough to meet the cumulative arrival rate of patients before the clinic stops accepting patients, this value will be when the service function equals the total number of patients plus the raw processing time. This is calculated as follows:

$$T_c = \begin{cases} T^* + B, & \mathrm{T}^* r_e \geq P_t \\ \frac{P_t}{r_e} + B, & \mathrm{T}^* r_e < P_t \end{cases}$$

$$\text{or } T_c = \max\{T^*, \frac{P_t}{r_e}\} + B$$

Average number of patients in the clinic ($\bar{P}$) - This is the estimated amount of patients that are in the clinic at any given time. This is calculated as follows:

$$\bar{P} = \tfrac{1}{T_c} \int_0^{T_c} (A(t) - D(t))dt$$

$A(t) - D(t)$ denotes how many people are in the clinic at any given time. There are two cases in calculating this. The first being where the service rate is high enough to catch up to the cumulative arrival rate before the clinic stops accepting patients ($T^* r_e \geq P_t$) and the second being where the service rate catches up to the total patients after the clinic stops accepting patients. If the first case, the $D(t)$ function will be piecewise-linear and must be calculated in separate parts.

The visual representation of the first case is shown in Figure 1.

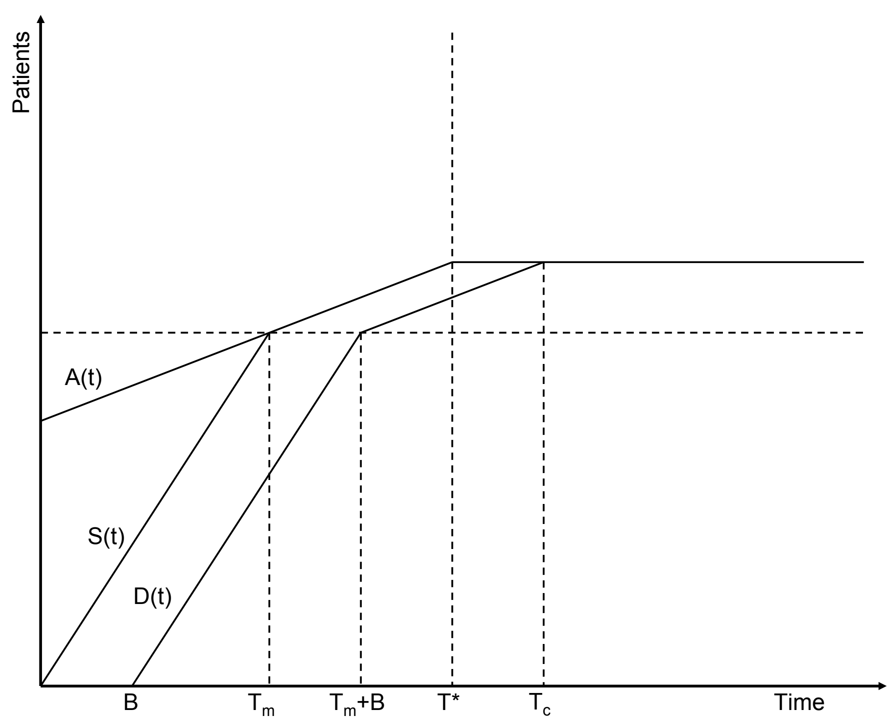


Figure 1: The arrival, service, and departure curves when $r_e T^* \geq P_t$.

To find the average amount of patients in this case, the values for the formula can be found the following way:

$$\int_0^{T_c} A(t)dt = (\tfrac{1}{2})(T^*)(P_0 + P_t) + (T_c - T^*)(P_t) = \tfrac{1}{2}T^*(P_0 + P_t) + BP_t$$

$$\int_0^{T_c} D(t)dt = (\tfrac{1}{2})(T_m)(S(T_m)) + (\tfrac{1}{2})(T_c - (T_m + B))(S(T_m) + P_t) = \tfrac{1}{2}r_eT_m^2 + \tfrac{1}{2}(T^* - T_m)(r_eT_m + P_t)$$

Where $S(T_m)$ is the number of patients in the clinic when the service rate is equal to the arrival rate. The visual representation of the second case is shown in Figure 2.

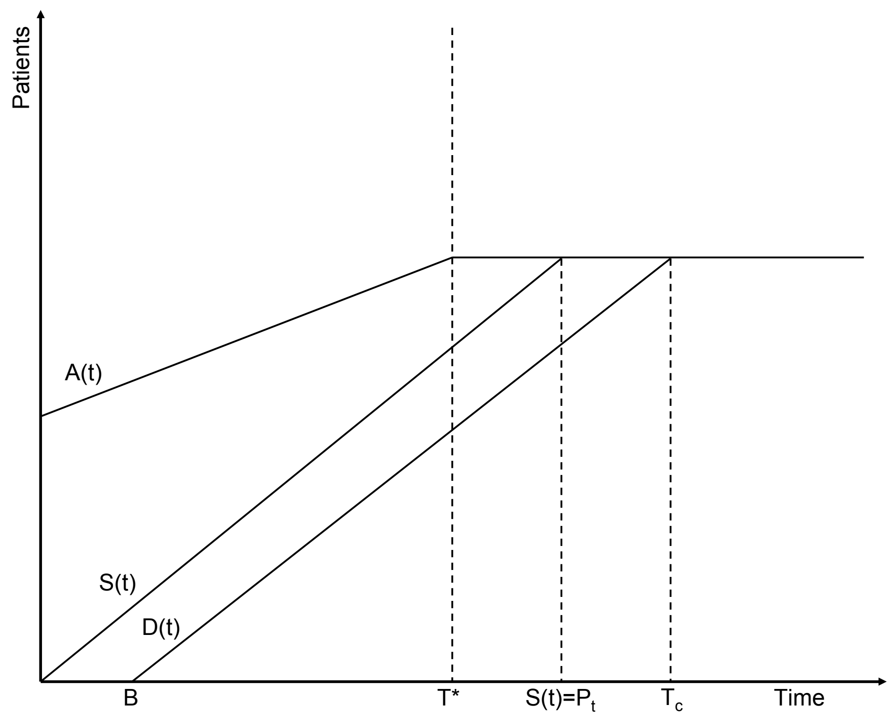


Figure 2: The arrival, service, and departure curves when $r_eT^* < P_t$.

To find the average amount of patients in this case, the values for the formula can be found the following way:

$$\int_0^{T_c} A(t)dt = (\tfrac{1}{2})(T^*)(P_0 + P_t) + (T_c - T^*)(P_t) = \tfrac{1}{2}T^*(P_0 + P_t) + (B + \frac{P_t}{r_e} - T^*)P_t$$

$$\int_0^{T_c} D(t)dt = (\tfrac{1}{2})(T_c - B)(P_t) = \frac{P_t^2}{2r_e}$$

Average time a patient spends in the clinic ($\bar{t}$) - This is the average time, in minutes, a patient spends in the clinic after entering. This is calculated as follows:

$$\bar{t} = \frac{60\bar{P}T_c}{P_t}$$

Bottleneck - This is the station with the smallest service rate. Station i is a bottleneck if and only if:

$$\frac{f_ir_{ei}}{\lambda_i} = r_e$$

5 Simulation Experiments

The Clinic Surge Planning Model calculates performance according to the inputs and the calculations presented in the previous section. To test the validity of this model, it is necessary to simulate two different clinics and compare the output. For simulation, Rockwell Arena will be used. A model of the clinic is created in a flow chart type representation and statistics are collected from random numbers generated by the software.

5.1 Howard County Drive-Through Clinic

The first clinic is modeled from statistics collected at the Howard County Drive-Through Clinic on October 15, 2006. This is not a typical model because the processing times are for carloads of people. Each statistic is for the processing of one car and assuming the driving speed is 10 miles per hour. The routing is in the following order with each station's flow leading into the next: Forms Distribution, Triage, Fees Payment, and Vaccination. For this particular simulation, the clinic plans to serve 900 patients with an initial surge of 200 patients with an accepting time of 4 hours. The inputs for the Excel Clinic Surge Planning Model are shown in Table 1.

Table 1: Howard County Drive-Through Flu Clinic Stations

Station	Mean Time (Minutes)	Number of Staff	Distance Leaving (Miles)
Forms Distribution	1.22	5	1.4
Triage	0.70	5	0.3
Fees Payment	0.63	5	0.1
Vaccination	1.65	6	0.3

The Clinic Surge Planning Model estimates that the clinic will be open 4.41 hours, the rate of service will be 218 patients per hour, the average number of patients in the clinic will be 161, and the average time a patient spends in the clinic is 47 minutes. Also, the bottleneck is predicted to be the Vaccination station.

Now the simulation will be run to measure for accuracy. The flowchart model can be seen in the Appendix in Figure 3. The Gamma Distribution for the processing average time and variance can be seen in Table 2.

Table 2: Gamma Distribution Inputs for Processing Blocks

Station	Beta (β)	Alpha (α)
Forms Distribution	0.2328	5.2254
Triage	0.3810	1.8373
Fees Payment	0.6052	1.0463
Vaccination	0.6768	2.4380

5.1.1 Simulation with Constant Arrival

The first simulation was run with constant arrival of the patients not included in the surge for the 4 hours that the clinic is accepting new patients.

Table 3: Drive-Through Clinic Simulation with Constant Arrival

	Time to Service Patients (hours)	Average Number of Patients	Average Time in Clinic (minutes)
CSPM Estimate	4.41	161	47
Averages	4.39	158	46
Sample Variance	0.01	87.82	13.52
95% Confidence Interval	0.08	6.70	2.63
Minimum Value	4.31	151.05	43.57
Maximum Value	4.46	164.45	48.83

We can see that the time to service patients, average number of patients, and average time in clinic were all in the confidence range output from the simulation. Also, the simulation showed that the Vaccination Station was also the bottleneck.

5.1.2 Simulation with Exponential Arrival

This simulation is run so that the arrival of cars into the clinic are exponentially distributed so that it is more realistic.

Table 4: Drive-Through Clinic Simulation with Exponential Arrival

	Time to Service Patients (hours)	Average Number of Patients	Average Time in Clinic (minutes)
CSPM Estimate	4.41	161	47
Averages	4.44	153	45
Sample Variance	0.00	374.02	31.28
95% Confidence Interval	0.03	13.83	4.00
Minimum Value	4.41	138.67	41.18
Maximum Value	4.47	166.34	49.18

Similarly to the previous simulation, all of the compared statistics from the planning model fall in the confidence range of the Arena output. Also, the Vaccination Station is also the bottleneck in this case. From these results we see that the planning model is a good indicator of performance when there is a clinic with high surge and simple routing.

5.2 Smallpox Vaccination Clinic

In the Howard County simulation, the CSPM was successful in estimating the clinic performance. Since this was a very simple simulation, a more complex one is required. The next clinic is modeled after an experiment of a smallpox vaccination clinic. This type of simulation is important because it is similar to what may happen if a bioterrorist attack were to cause the release of smallpox into a population. In this particular case there will be 1,020 patients vaccinated with three hours to accept them into the clinic. The average times, staffing, and batch sizes can be seen in Table 5.

Table 5: Smallpox Vaccination Clinic Stations

Station	Mean Time (Minutes)	Number of Staff	Batch Processing Size
Triage (a)	0.26	5	1
Symptoms Room (b)	1.21	3	1
Holding Room (c)	3.80	3	1
Registration (d)	0.12	8	1
Education (e)	24.00	8	30
Screening (f)	1.72	9	1
Consultation (g)	3.77	6	1
Vaccination (h)	3.26	16	1

Unlike the Howard County Drive-Through clinic, the routing is more complex and can be found in Table 6.

Table 6: Routing Table for Small Pox Clinic

				To				
From	b	c	d	e	f	g	h	Exit
a	0.048	0.032	0.920	0	0	0	0	0
b		0	0.67	0	0	0	0	0.33
c			0.65	0	0	0	0	0.35
d				1.00	0	0	0	0
e					1.00	0	0	0
f						0.262	0.738	0
g							0.941	0.059
h								1.00

When there is no surge, the CSPM estimates that the time needed to serve all patients is 3.81 hours, the service rate is 307 patients per hour, the average number of patients in the clinic is 175, and the average time a patient spends in the clinic is 39 minutes. Also, the bottleneck is estimated to be the Vaccination station. Where there is a planned surge of 300, the CSPM estimates that the time needed to serve all patients is 3.81 hours, the service rate is 307 patients per hour, the average number of patients in the clinic is 293, and the average time a patient spends in the clinic is 66 minutes. In this case, the bottleneck is also estimated to be the Vaccination station.

The input data for the processing blocks in the Arena simulation can be seen in the following table:

Table 7: Distribution Inputs for Processing Blocks

Station	Processing Time Distribution (min.)
Triage	0.125+EXPO(0.134)
Symptoms Room	0.59+EXPO(0.623)
Holding Room	EXPO(3.8)
Registration	0.025+EXPO(0.0995)
Education	18+EXPO(6)
Screening	0.999+GAMM(1.07,0.678)
Consultation	GAMM(1.16,3.25)
Vaccination	1+GAMM(0.581,3.89)

5.2.1 Simulation with No Surge and Constant Arrival

The first two simulations will test the CSPM for accuracy when looking at a case with no surge. The first is with a constant arrival of the 1,020 patients over the period of the three hours.

Table 8: Smallpox Clinic Simulation with No Surge and Constant Arrival

	Time to Service Patients (hours)	Average Number of Patients	Average Time in Clinic (minutes)
CSPM Estimate	3.81	175	39
Averages	3.94	197	46
Sample Variance	0.00	79.42	6.44
95% Confidence Interval	0.04	6.37	1.81
Minimum Value	3.90	190.22	43.85
Maximum Value	3.98	202.97	47.47

The CSPM poorly estimated the performance of the clinic. All of the estimates were below the confidence range of values output from the Arena simulation. Similarly to the CSPM findings, the Arena simulation did find that the Vaccination station was the bottleneck.

5.2.2 Simulation with No Surge and Exponential Arrival

This simulation is run one more time with the arrivals exponentially distributed for a more realistic run.

Table 9: Smallpox Clinic Simulation with No Surge and Exponential Arrival

	Time to Service Patients (hours)	Average Number of Patients	Average Time in Clinic (minutes)
CSPM Estimate	3.81	175	39
Averages	3.99	205	48
Sample Variance	0.01	320.03	23.52
95% Confidence Interval	0.07	12.80	3.47
Minimum Value	3.91	192.55	44.71
Maximum Value	4.06	218.15	51.65

The same results are seen as with the previous simulation. There are different possibilities for the error in planning with the CSPM. This maybe because of the complexity of the model. Also, since the conveyor model requires a highly constant amount of patients being serviced, the clinic doesn't start running with a high number of patients until well after the clinic starts accepting patients. In this case, it may be better to use a different planning model.

5.2.3 Simulation with a Surge and Constant Arrival

Now the CSPM is tested against the simulation when there is an initial surge of 300 patients.

Table 10: Smallpox Clinic Simulation with a Surge and Constant Arrival

	Time to Service Patients (hours)	Average Number of Patients	Average Time in Clinic (minutes)
CSPM Estimate	3.81	293	66
Averages	3.84	278	63
Sample Variance	0.00	119.21	9.44
95% Confidence Interval	0.04	7.81	2.20
Minimum Value	3.80	269.79	60.38
Maximum Value	3.87	285.41	64.78

In this case we see that the CSPM is more accurate in predicting the results of the simulation. The time to service patients is in the confidence range from the Arena output. The average number of patients and average time in clinic are above the confidence range but closer than the previous simulations without a surge. The bottleneck in this case is the Vaccination station.

5.2.4 Simulation with Surge and Exponential Arrival

Now this simulation is run with a surge and exponentially distributed arrival of patients.

Table 11: Smallpox Clinic Simulation with a Surge and Exponential Arrival

	Time to Service Patients (hours)	Average Number of Patients	Average Time in Clinic (minutes)
CSPM Estimate	3.81	293	66
Averages	3.87	278	63
Sample Variance	0.01	253.54	5.76
95% Confidence Interval	0.09	11.39	1.72
Minimum Value	3.78	266.58	61.46
Maximum Value	3.96	289.36	64.90

In this case the results were similar to the previous simulation. The time to service all patients was within the confidence range, but the other two measurements were above the prediction. This shows that the CSPM does not perfectly estimate the performance of the clinic, but performs better when there is a surge of patients before the clinic opens. This is probably because the model performs best when there is a highly constant amount of patients since the mathematical calculations are based on the conveyor model.

5.3 Second Smallpox Simulation

To go further with these results, it was necessary to see where the CSPM performs well when there is no surge. Two more simulations were run with all of the same parameters except that 2,040 patients will be served with no surge. This is done to see if this will satisfy the 'conveyor model' restriction of needing a highly-constant amount of patients. The CSPM shows that the clinic will need 7.13 hours to service all patients, the service rate will be 307 patients per hour, the average number of patients in the clinic will be 662, and the average time a patient spends in the clinic will be 139 minutes. As before, the Vaccination station will be the bottleneck in this case.

5.3.1 Simulation with Constant Arrival

The first simulation is run with a constant arrival of patients for the three hours.

Table 12: Second Smallpox Vaccination Clinic Simulation with Constant Arrival

	Time to Service Patients (hours)	Average Number of Patients	Average Time in Clinic (minutes)
CSPM Estimate	7.13	662	139
Averages	7.17	644	136
Sample Variance	0.01	153.06	14.12
95% Confidence Interval	0.06	8.85	2.69
Minimum Value	7.11	634.82	132.97
Maximum Value	7.23	652.52	138.35

This simulation is more successful since the time to service patients falls within the confidence range output from the Arena data. The average number of patients and average time a patient spends in the clinic is still higher than the confidence range.

5.3.2 Simulation with Exponential Arrival

One more simulation is run with the arriving patients being exponentially distributed.

Table 13: Second Smallpox Vaccination Clinic Simulation with Exponential Arrival

	Time to Service Patients (hours)	Average Number of Patients	Average Time in Clinic (minutes)
CSPM Estimate	7.13	662	139
Averages	7.20	651	138
Sample Variance	0.00	178.19	11.56
95% Confidence Interval	0.05	9.55	2.43
Minimum Value	7.16	641.13	135.51
Maximum Value	7.25	660.23	140.37

In this case, the CSPM accurately predicted the average time a patient spends in the clinic within the confidence range and the other measures close to the confidence range. Although the CSPM is not completely accurate in predicting these results, we see that it can be close when planning a clinic with no surge and a high arrival rate.

6 Summary and Conclusions

Models like the CSPM are very important. In many instances, there is a need for a tool to quickly set-up and estimate performance of a clinic needed to vaccinate a large population in a short period of time. This particular model was built to compensate for an initial surge of patients waiting before the clinic is open because other models can not accurately calculate the performance. The CSPM is based on the conveyor model because queues are not considered and a highly constant amount of patients are needed for the calculations to be close.

In the case of the simpler Howard County Drive-Through Clinic, the CSPM accurately predicted the Arena output. In the case of the more complex Smallpox Clinic, the results were not as accurate but closer in the cases where there was a surge or high arrival rate of patients. Although this is true, the CSPM would be helpful in planning clinics because in all cases the bottleneck was accurately predicted and this would allow clinic planners to assign more staff to these stations if needed. Also, in many simulations of the Smallpox Clinic, the CSPM did not accurately estimate performance within the confidence interval, but it would be close enough for clinic planners to have a good idea of how their clinic will perform. The simulations showed that this model should be used only if there will be a surge of patients before the clinic opens or a large amount of patients to keep all the stations busy because this is when they are most accurate.

This exercise and activity during the REU gave me great experience with research and clinic planning. I am now more sure than ever this is exactly what I want to do in my future. I feel as though clinic planning, and healthcare optimization in general, is a great area for academic research to focus because the health of our citizens is a great place to utilize our resources.

Appendix

7 Flow Chart Models

Figure 3: Howard County Drive-Through Clinic Simulation Model

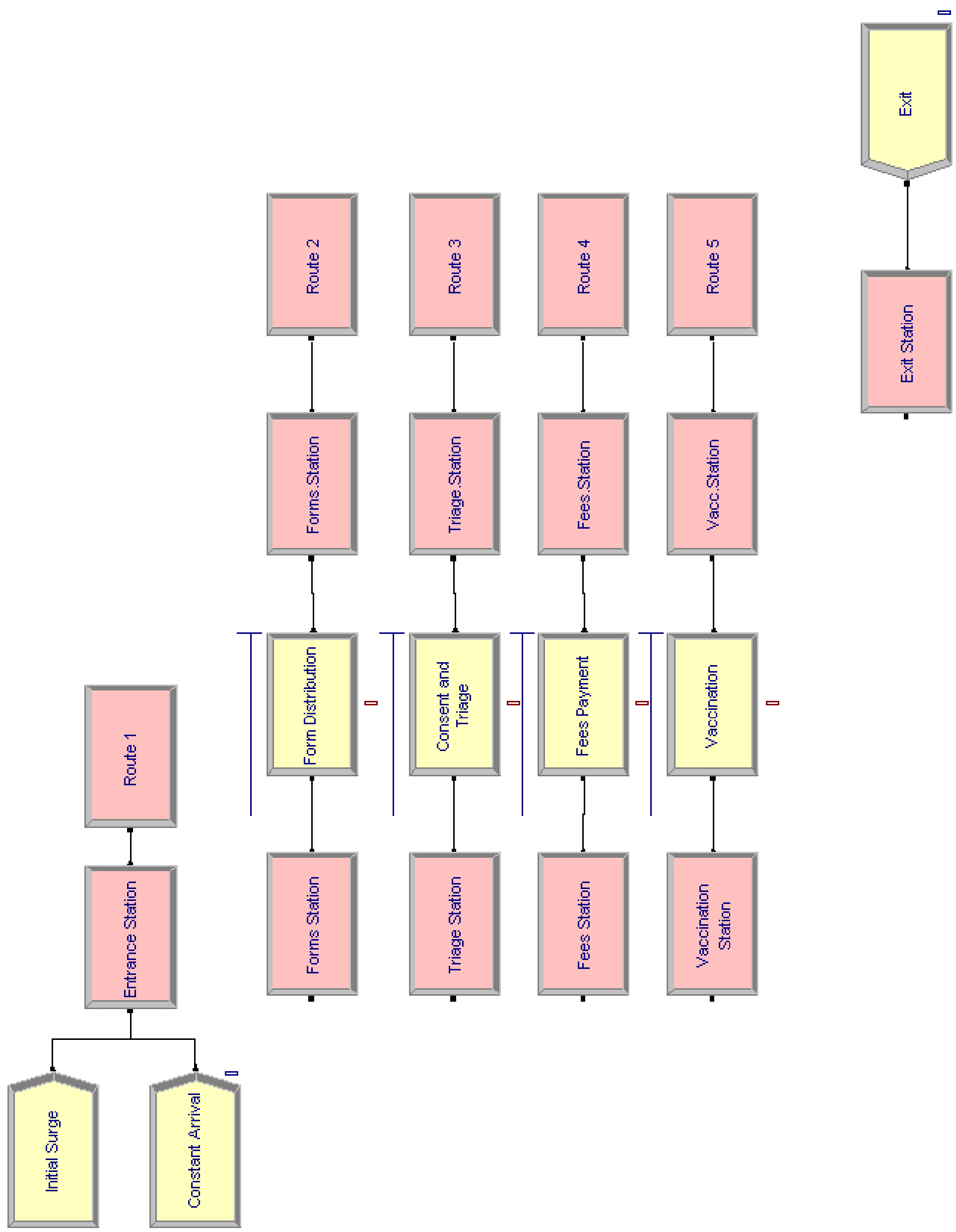
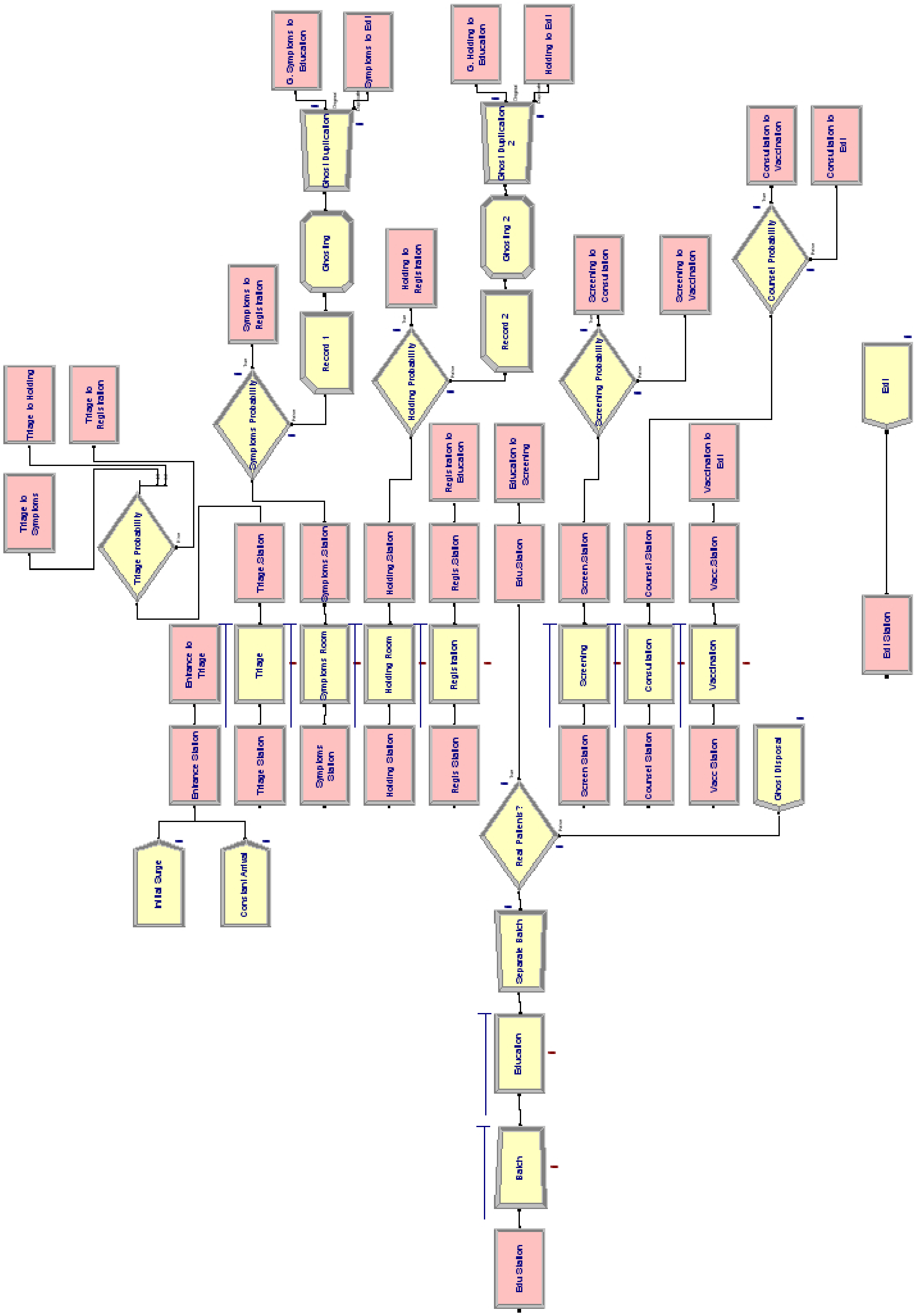


Figure 4: Small Pox Clinic Simulation



8 Acknowledgements

Thanks for the Institute for System Research's REU program, my advisor Dr. Jeffrey Herrmann, Ali Pilehvar, and Peter Lin for this opportunity.

References

[1] Aaby, K.; Herrmann, J.W.; Jordan, C.S.; Treadwell, M.; and Wood, K. "Montgomery County's Public Health Service Uses Operations Research to Plan Emergency Mass Dispensing and Vaccination Clinics," *Interfaces*, Vol. 36, No. 6, pp. 569-579, 2006.

[2] CDC Smallpox - Maxi-Vac, http://www.bt.cdc.gov/agent/smallpox/vaccination/maxi-vac, July 31, 2007.

[3] Computer Staffing Model for Bioterrorism Response, http://www.ahrq.gov/research/biomodel.htm, July 31, 2007.

[4] Herrmann, Jeffrey W. "Time Study Analysis, Drive-through Flu Clinic, Columbia, Maryland," 2006.

[5] Herrmann, J.W.; Pilehvar, A.; and Treadwell, M.A. "Queueing Network Approximations for Mass Dispensing and Vaccination Clinics," 2006.

[6] Hopp, W.J. and Spearman, M.L. 2001, *Factory Physics, Second Edition*, Irwin/McGraw-Hill, New York.

[7] Johnson, Richard A. 2000, *Miller & Freund's Probability and Statistics for Engineers, Sixth Edition*, Prentice Hall, Upper Saddle River, NJ.

[8] Kelton, W.D.; Sadowski, R.P.; and Sturrock, D.T. 2007, *Simulation with Arena, Fourth Edition*, McGraw-Hill, New York.