SIMULATION MODELING PROJECT

Ticket Athletic Office: University of Cincinnati

Adrian Valles

MS Business Analytics: University of Cincinnati

TABLE OF CONTENTS

Chapter 01: Introduction and problem statement

1.1 Introduction

This simulation study, part of the Simulation Modeling and Methods class (BANA 7030), simulates the operations of the ticket athletic office of the University of Cincinnati prior to a Saturday Football home game. This study uses 'Arena', which is a simulation software owned by Rockwell automation. Because most of the transactions prior to a home game involve the disposal of the 2000 free student tickets, this model captures the activity of the ticket office from Monday at 8.am, when the disposal of the free tickets starts, until they are all given away (or until Friday at 5p.m if this limit hasn't been reached). Data was collected regarding the arrival times of the walk-in customers, phone calls and online transactions as well as the service time for each customer and phone call during the rush hours on Monday morning. Once the model is built (imitating the functioning of the athletic office) and the data inputted, 'Arena' gives statistical accumulators such as wait time in queue by customers, elapsed time of the simulation, utilization of the resources…etc.

1.2 Problem statement

The bad results of the football program are having an impact in the demand of tickets for the home games. In fact, there has been a substantial drop in the number of spectators that attended the last football games and the athletic department is concerned about it. Consequently, they have realized there is a potential need for the ticket athletic office to adjust some expenses to the new fans shortage situation as they have realized that their ticket office strategy might only be efficient for high-demand games.

Given the unique and inflexible ticket office strategy, I was commissioned by the athletic department to run a simulation study on the ticket athletic office to determine whether the current ticket office strategy works also well for low-demand games, and second, whether an alternative strategy can be implemented to improve the efficiency of the ticket office during low demand games.

1.3 Ticket office operation and model assumptions

The ticket athletic office operates in the following way: Free student tickets are available since 8.am on the Monday prior to the game and students can either go to the ticket office to get their tickets or get them through an online transaction. Approximately 75% of the students do it online. The athletic ticket office has 4 ticket officers working from 8a.m to 2p.m on Monday (Period one), 3 students from 2 p.m. to 5p.m on Monday (Period two), and only 2 students for the rest of the week, working from 8a.m on Tuesday to 5p.m on Friday (Period three). Ticket officers make 8.10$ per hour.

Online transactions don't involve the use of any ticket officer. However, walk in customers do. Approximately 90 % of the walk-in customers are students that claim their free-student ticket, and the remaining 10% are customers that go to the ticket office for other reasons, such as to buy non-complimentary tickets for the football and basketball games.

Another factor to take into consideration is the incoming phone calls to the ticket athletic office. While free student tickets cannot be given away through phone calls, other non-complimentary tickets can. Phone calls are taken by the student ticket officers, and as long as there is a phone line open, the ticket officers take the call. However, if there are walk-in customers, the call is put on hold until there are not walk-in customers left. There are as many phone lines as ticket officers in the system (4 for period one, 3 for period two and 2 for period 3). Simulation ends when 2000 entities looking for free student tickets have entered the system (or at 5p.m on Friday otherwise).

In order to model this system, I have made the following assumptions:

1. For convenience reasons, I have divided the week into three periods, based on the number of ticket officers available at each time on the office as Table 1.1 shows.

Period	# Ticket Officers	Schedule
1	4	Monday 8a.m-2p.m
2	3	Monday 2p.m-5p.m
3	2	Tuesday 8a.m-end

Table 1.1. Different number of ticket officers are used for different periods of time

2. Ticket officers don't take breaks.
3. The ticket officer's weekly allocation is kept the same until the end of the week, even if the free tickets sell out.
4. There is no economic cost associated with missing calls.
5. All customers that are put on hold are assumed to wait patiently until the ticket officer is available.
6. The athletic department can predict whether a game is expected to have low or high demand based on the results from that season, weather forecast and the rival team.
7. Wednesday, Thursday and Friday's data has been imputed from Tuesday.
8. The 11-2p.m shift has been assumed to have the same arrival times than the 8-11a.m shift.
9. Percentage drop of the interarrival times for the afternoon (2-5p.m) shift has been estimated based on the assistant ticket officer assistant director's prior experience.

Chapter 02: Data collection

2.1 Data Collection

One of the most critical steps of the study is to get the specific data needed to build the model. I collected data for the interarrival time of the walk-in customers, phone-calls as well as their service times. Finally, I also collected the type of transaction of the walk-in customers, and I found that, over the course, 90% of them want free student tickets. The data regarding online transactions was given to me by the ticket athletic office. Data was collected from 8-10a.m, during rush hours, on Monday November 6th and from 9-10a.m on Tuesday November 7th.

Two important decisions were made regarding the arrival times of the transactions involving free student tickets. This includes the arrival times of the walk-in customers and the arrival times of the online transactions. Due to the limitation of the free tickets, students tend to get them Monday morning, creating rush hours during this time. Consequently, both the arrival times of walk in customers and the arrival of online transactions follow non-stationary patterns and therefore they have been modeled using a non-stationary Poisson process as it will be explained in Tables 2.1 and 2.2 of section 2.3.

2.2 Stationary Processes-Input analyzer

We will start the process of fitting a distribution to the data by analyzing those processes that are stationary. For these types of processes, I have used input analyzer, which is a built-in Arena tool that facilitates the process of fitting a probability distribution to my data. The input analyzer fits many distributions to the data and selects the most appropriate one.

For instance, Figure 2.1 shows the histogram as well as summary of the data characteristics with the expression of the most appropriate distribution to fit the Phone call interarrival times.

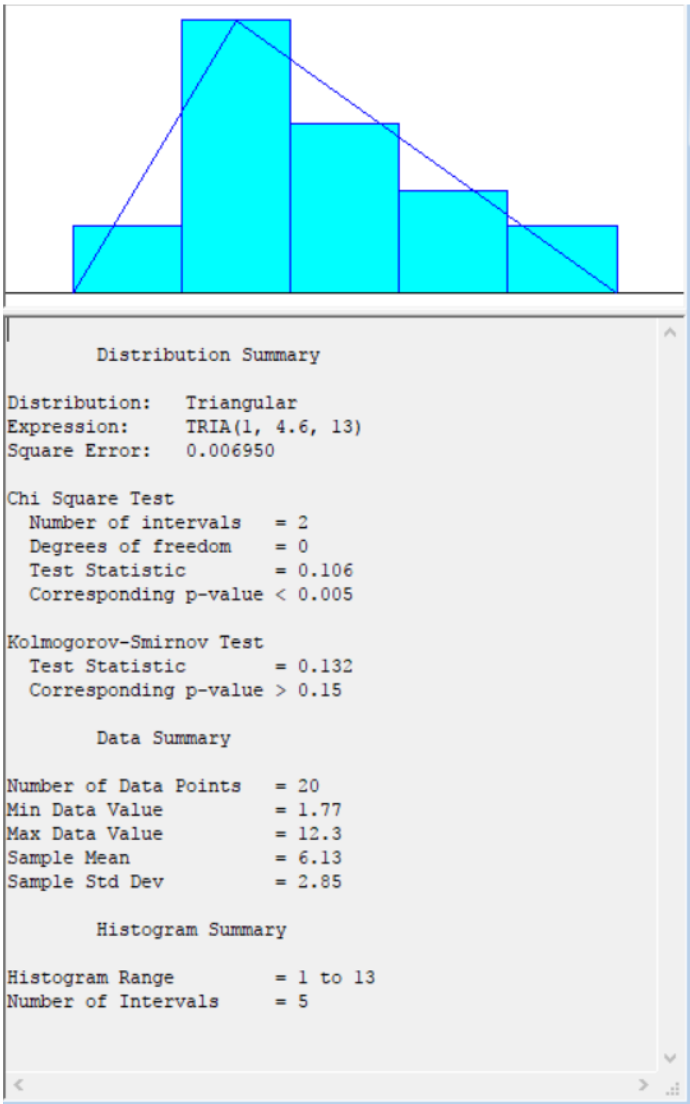
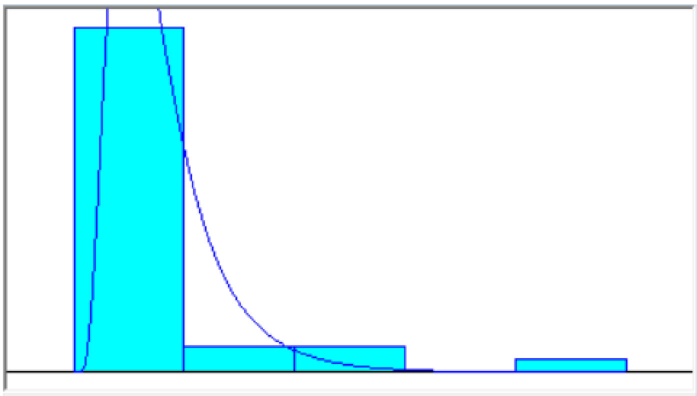


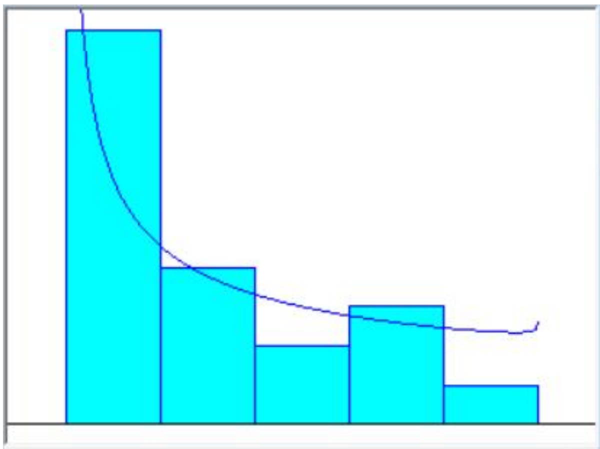
Figure 2.1. Histogram and Summary of the Phone calls Interarrival times (in minutes)

Next, using input analyzer once again, we will get expressions for both service times of the walk-in customers as well as service times of the phone calls. Figures 2.2 and 2.3 show this.



```
        Distribution Summary

Distribution:   Lognormal
Expression:     LOGN(0.77, 0.477)
Square Error:   0.031021

Chi Square Test
  Number of intervals    = 2
  Degrees of freedom     = -1
  Test Statistic         = 4.49
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic         = 0.218
  Corresponding p-value = 0.0848

        Data Summary

Number of Data Points    = 32
Min Data Value           = 0.35
Max Data Value           = 4.5
Sample Mean              = 0.823
Sample Std Dev           = 0.826

        Histogram Summary

Histogram Range          = 0 to 4.92
Number of Intervals      = 5
```

Figure 2.2. Histogram and summary of the walk-in customers service time (in minutes)



```
Distribution:   Beta
Expression:     1 + 10 * BETA(0.537, 0.977)
Square Error:   0.007885

Chi Square Test
  Number of intervals   = 2
  Degrees of freedom    = -1
  Test Statistic        = 0.386
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.121
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 20
Min Data Value          = 1.08
Max Data Value          = 11
Sample Mean             = 4.02
Sample Std Dev          = 2.82

        Histogram Summary

Histogram Range         = 1 to 11
Number of Intervals     = 5
```

Figure 2.2. Histogram and summary of the phone calls service time (in minutes)

2.3 Non-Stationary Poisson Processes

As discussed earlier, the arrival times of both walk-in customers and online transactions have been modeled using a non-stationary Poisson process. Particularly, in the case of the walk-in customers arrivals, not only the limitation of the free student tickets makes the process non-stationary (creating rush hours on Monday morning), but also the University class schedule influences the student arrivals to the office. For instance, the number of walk-in customers between 9.30-10a.m is double than the one between 9-9.30. This partially occurs because students decide to pick up their tickets before going to their 10. 05a.m class. On the other hand, between 9-9.30 students are normally either in class or about to leave their houses for the 10.05 class. Therefore, classes schedule has an influence on the arrival of the walk-in customers (90% are students) to the ticket office.

Data for walk-in customers has been collected in arrivals per hour for each 30-minute period during which the system is open. Some assumptions have been made such as the arrival rates are the same for the 8-11a.m than the 11a.m to the 2p.m shifts and there is a drop of about 20% during the afternoon shift (2p.m to 5p.m). Also, we assume the arrival rates are the same from Tuesday to Friday with a 50% drop in the rates compared to Monday. These walk-in arrival rates are given in the tables 2.1.

	Monday	Tuesday	Wednesday	Thursday	Friday
Time	**Rate(arr/hr)**	**Rate(arr/hr)**	**Rate(arr/hr)**	**Rate(arr/hr)**	**Rate(arr/hr)**
8:00-8:30	32	16	16	16	16
8:30-9:00	38	18	18	18	18
9:00-9:30	22	10	10	10	10
9:30-10:00	44	22	22	22	22
10:00-10:30	30	14	14	14	14
10:30-11:00	36	18	18	18	18
11:00-11:30	32	16	16	16	16
11:30-12:00	38	18	18	18	18
12:00-12:30	22	10	10	10	10
12:30-1:00	44	22	22	22	22
1:00-1:30	30	14	14	14	14
1:30-2:00	36	18	18	18	18
2:00-2:30	28	12	12	12	12
2:30-3:00	30	12	12	12	12
3:00-3:30	18	6	6	6	6
3:30-4:00	36	18	18	18	18
4:00-4.30	24	10	10	10	10
4:30-5:00	28	12	12	12	12

Table 2.1. Walk-in Arrival rates (Arrivals Per Hour)

Regarding online transactions, data has been modeled in transactions per hour for 1-hour periods during which the system is open. The rates in table 2.2 shows the Monday morning rush hours. Transaction rates from Tuesday to Friday have been assumed to be equal.

	Monday	Tuesday	Wednesday	Thursday	Friday
Time	**Rate(arr/hr)**	**Rate(arr/hr)**	**Rate(arr/hr)**	**Rate(arr/hr)**	**Rate(arr/hr)**
8:00-9:00	120	50	20	20	20
9:00-10:00	150	20	20	20	20
10:00-11:00	100	20	20	20	20
11:00-12:00	80	20	20	20	20
12:00-1:00	70	20	20	20	20
1:00-2:00	60	20	20	20	20
2:00-3:00	60	20	20	20	20
3:00-4:00	50	20	20	20	20
4:00-5:00	50	20	20	20	20

Table 2.2. Online transaction rates (Calls Per Hour)

Chapter 03: Arena Model

3.1 Overall Picture

In order to construct a model that imitates the functioning of the athletic ticket office, the simulated model is divided into modules that imitate different function of the system. The purpose of these modules is to make the individual operations (arrivals, service times, etc.) occur as they would in the real world. The different modules will be further explained in this chapter.

An overall procedure of the simulated ticket athletic has the next steps: (In the subsections of this chapter, each step will be treated and explained more in depth)

1. Entities enter the system. There are three different types of entities: Phone calls (Blue box of figure 3.1), walk-in customers (Green box of figure 3.1), and online transactions (Red box of figure 3.1).
2. Phone calls and Walk-in customers are directed to the athletic ticket office (Grey box of Figure 3.3) and make use of the ticket officers. This results on sharing the same queue.
3. Online transactions are modeled apart because they don't use the resources of the ticket office. They are assumed to be instantaneous processes, so, as soon as they enter the system, they leave it.
4. After Phone calls and Walk-in customers are done with the service in the ticket office, they leave the system.

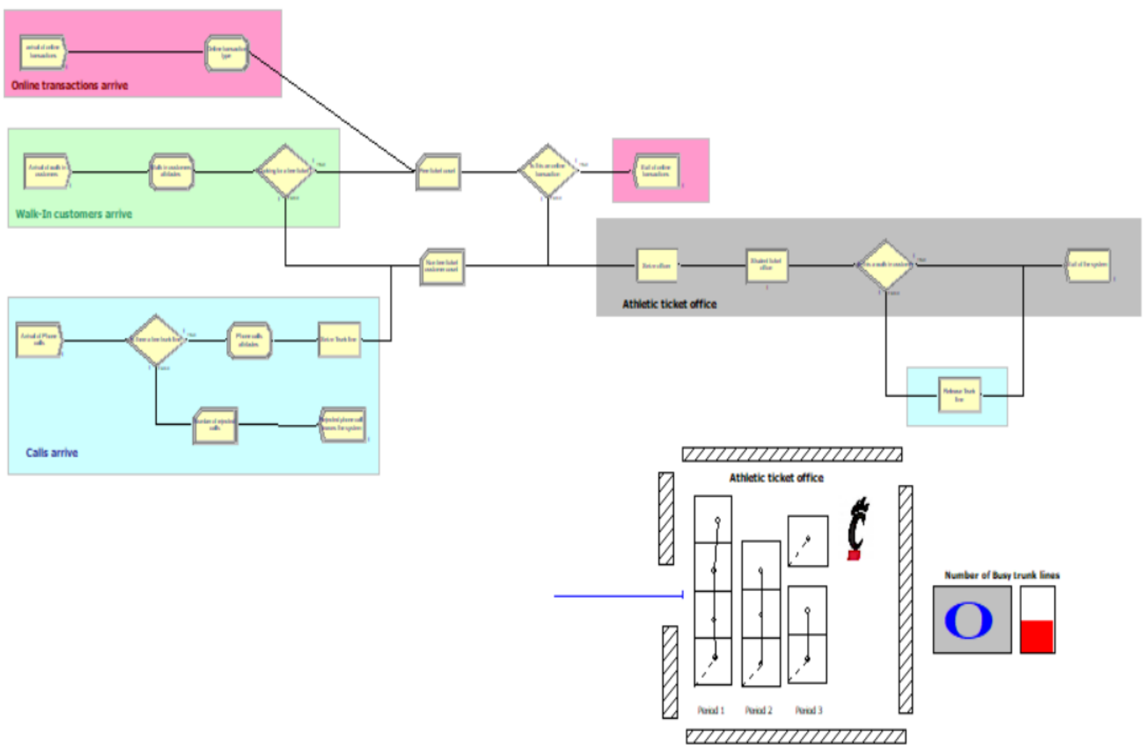


Figure 3.1. The final Arena model

3.2 Phone calls

Phone calls enter the system through the Create module called *Arrival of Phone calls* as given in Figure 3.2. In this Create module, I have specified that the arrival of the phone calls follow the distribution that I obtained using the input analyzer (Figure 2.1 of section 2.2). Then, the incoming calls go to a Decide module called *Is there a free trunk line* as given in figure 3.2 that checks the availability of the lines. Remember that there are as many trunk lines as officers working at that time (4 for period 1, 3 for period 2 and 2 for period 1). Therefore, the condition stated for this model is that if the current number of busy trunk lines is lower than the current number scheduled, the condition is true and therefore the trunk line proceeds to be seized. On the other hand, if there are not available lines, the condition is false, and the call is rejected. On this case, the phone call passes through a record module, *Number of rejected calls,* that simply counts how many phone calls have been rejected. Then, it leaves the system through the dispose module *Rejected phone calls leave the system,* as given in figure 3.2.

If a trunk line is available, we allow the entity to proceed to the seize module, *Seize Trunk line* from figure 3.2, where we seize that phone line. Right before this, the phone call had entered an assign module, *Phone calls attributes,* where we specified the distribution that these entities will follow during service time in the ticket office. Remember that this distribution was obtained from the input analyzer as given in figure 2.2 of section 2.2. In this module, we also give an entity type attribute to the phone calls to differentiate them from the walk-in customers. This differentiation will allow us to set a queue based on priority levels, as it will be explained during the ticket office section.

One important remark that needs to be addressed is that if a trunk line is seized and all the ticket officers are currently busy, the phone call is put on hold until the officer is done with the walk-in customers.

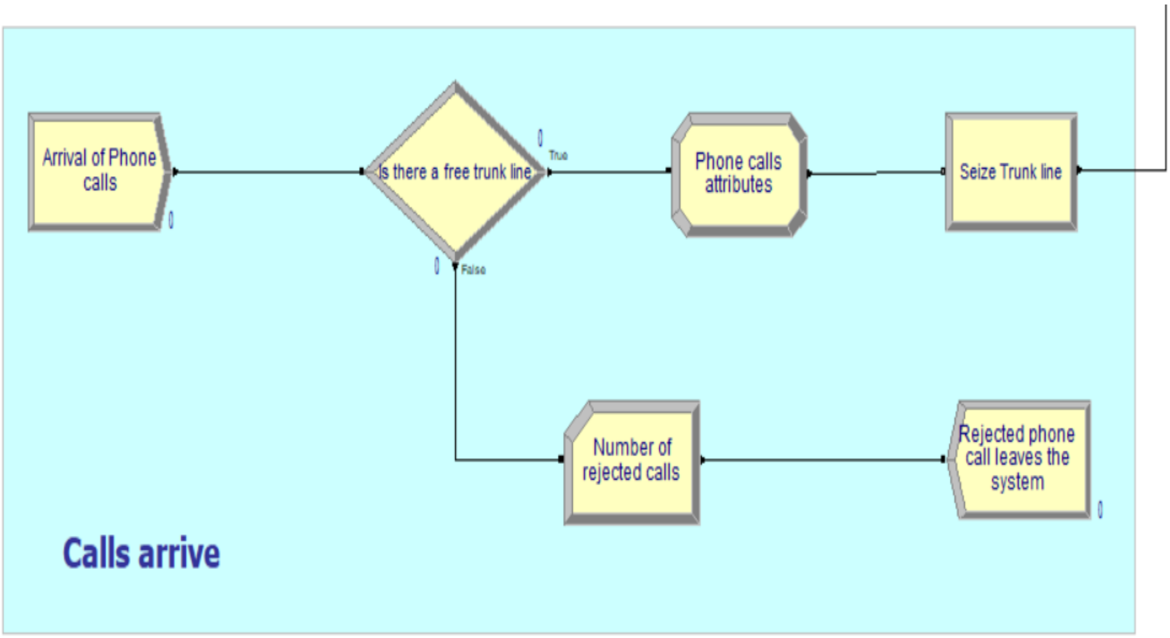


Figure 3.2. Phone calls part of the model

3.3 Walk-In Customers

The next type of entities are the walk-in customers. Similar than the incoming phone calls, they enter the system through a create module, *Arrival of Walk in customers* as given in Figure 3.3, where we have defined the distribution that these arrivals follow using a prespecified *Schedule*. Recall from section 2.3 that the arrival of Walk in customers follows a non-stationary Poisson process. Next, such as we did with the phone calls, we assign the Service time and the entity type through an Assign module, *Walk in customers attributes*. Then, these entities are sent to a decide module, *looking for a free ticket,* where the customer interest on a free ticket is determined according to the probabilities stated. On this Decide module, we selected the *2 way by chance* type and specified a percentage of 90, which represents the percentage of a customer wanting a free student ticket, involving that 10% of the customers don't look for one. Given that the condition is true, the customer is sent to the record module (Free *ticket count* as shown in Figure 3.3) that essentially counts the number of entities that have entered the system looking for a free student ticket. Recall that there are only 2000 free tickets available and when this counter gets to that number, the system is stopped. As we will see in the next section, all the online transactions pass through this record module. On the other hand, approximately 10 percent of the customers are sent to the *Non free ticket customer count* Record module, which is shared with all the non-rejected phone calls and it just determines the number of entities that have entered the system and are not interested in a free student ticket.

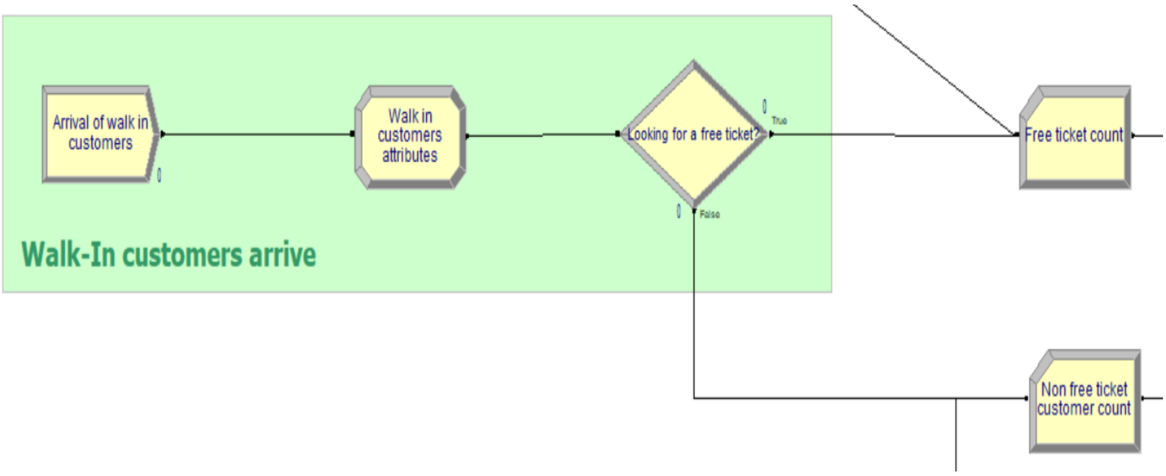


Figure 3.3. Walk-In Customers part of the model

3.4 Online transactions

The third and last type of entities are the online transactions, which involve only free tickets transactions. As it is given in Figure 3.4, the entities enter the system through the *Arrival of online transactions* Create module, following the Non-stationary Poisson Schedule that we defined in section 2.3. Then, the entities are sent to the Assign module *Online transaction* where the entity type is defined. Once the online transactions have passed through the free ticket counter, similar than the Walk-in customer, both Online transactions and Walk in customers are sent to the Decide module, *Is this an online transaction.* This Decide module, which is of *2 way* *by condition type,* simply divides the entities given their entity type attributes specified in the Assign modules. Therefore, the condition of all online transactions is true and they proceed to leave the system. On the other hand, all walk-in customer's condition is false, and they are sent to the athletic ticket office.

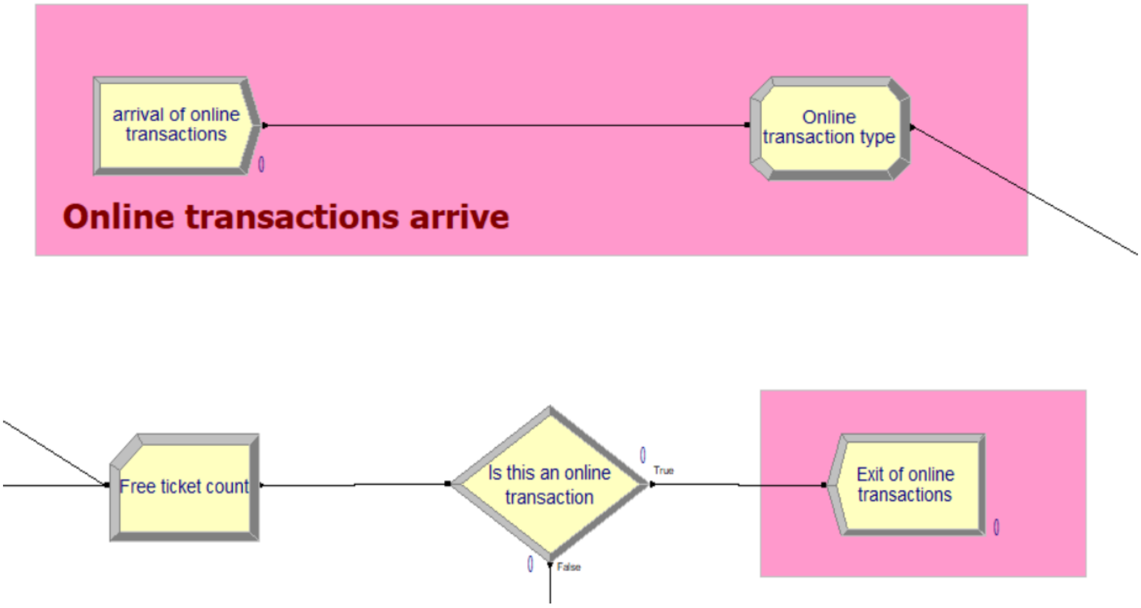


Figure 3.4. Walk-In Customers part of the model (Divided). After the Assign Module *Online transaction type*, all the online transactions are sent to the Record module, *Free ticket count*

3.5 Athletic Ticket Office

Finally, both non-rejected phone calls and Walk in customers are sent to the Ticket Office. The first step is to seize an officer through the *Seize Officer* Seize Module as given in Figure 3.4. Logically, the capacity of the officers is limited with a different level of availability depending on the period (given in Table 1.1). This implies that a queue is formed when all the ticket officers are busy. This queue is set to give priority to the Walk-in customers versus the phone calls. This involves that no phone call is taken while there are Walk in customers in line. Consequently, as we discussed earlier, phone calls are put on hold until a ticket officer is available. However, once a ticket officer has answered a call, the phone call is carried out even if physical customers walk in. Once an officer has been seized, the entity is sent to the Process Module *Student Ticket officer,* which simulates the service time spent by a Walk-in customer or Phone call in the Ticket Office. The service time attributes that we specified earlier allow the Process module to identify what service time expression should be used for each type of entity. Finally, once the service is finished, the entities are sent to the Decide Module *Is this a walk-in customer* module to determine the entity type. If true, Walk-In Customers simply exit the system through the *Exit the system* Release Module. If false, Phone calls release the trunk line before leaving the system through the same Dispose Module.

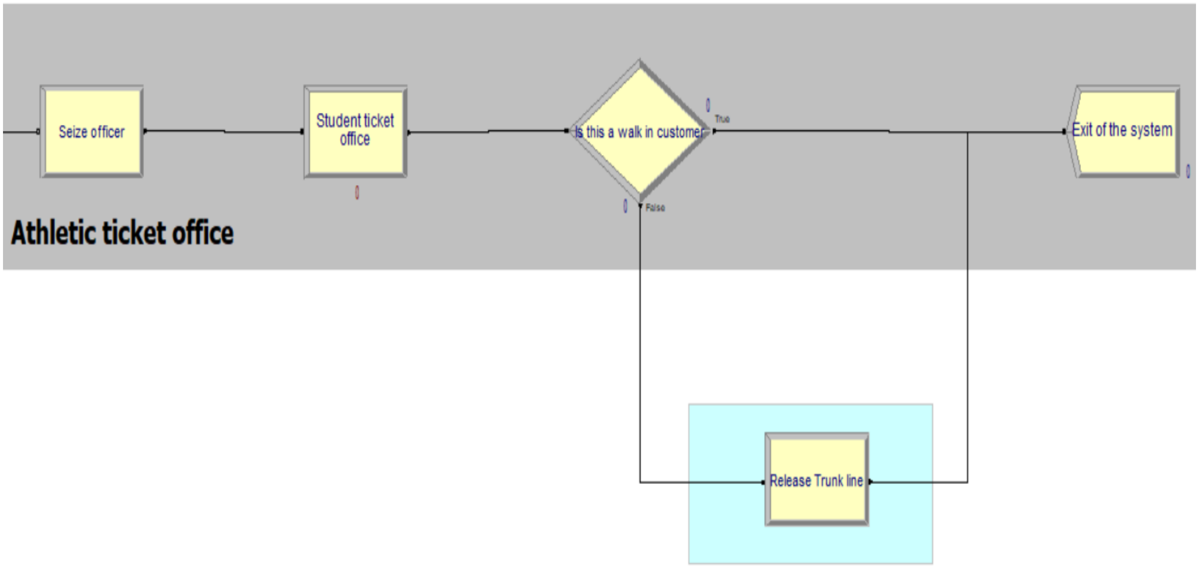


Figure 3.5. Athletic Ticket office part of the model

3.6 Animation

For debugging purposes, the Ticket Athletic office has been animated as given in Figure 3.6. The figure shows the animation at a time of period one when 1 phone call and 1 Walk-in Customer are in the system. This involves that at this point, 2 Ticket Officers are available and logically there is no a queue in the system.

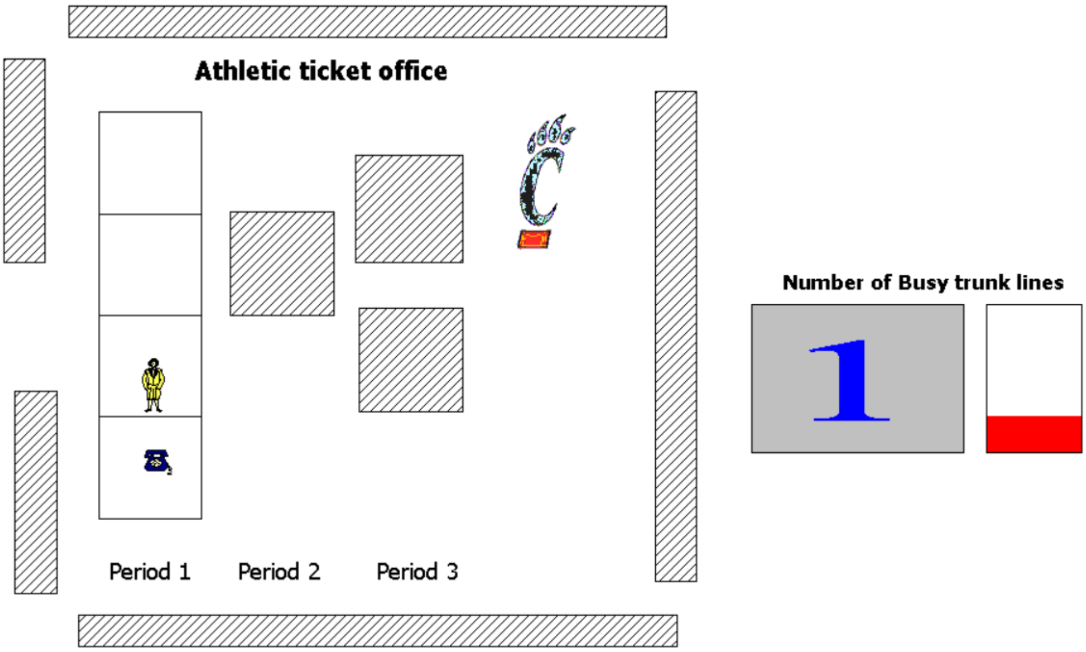


Figure 3.6. Animation of the Athletic Ticket Office

Chapter 04: Model Results and athletic department response

4.1Model Results

Given a stopping rule of whichever comes first between number of entities entering the system looking for a free ticket equal to 2000 or Friday at 5p.m, some of the most relevant results obtained after running the simulation for 100 replications are the following:

First and foremost, the athletic department is particularly interested with the time elapsed between the start and the end of the simulation. This allows the athletic department to have an approximation of the level of demand to expect for the game. For instance, high demand games give away all the free tickets by Tuesday, while low demand games don't give them away until the end of the week. An early disposal of the free tickets is ideal because it allows the athletic office to start selling overflow student tickets (10$) earlier in the week, which helps with the tickets revenue.

Unfortunately, as expected by the athletic department, the bad results of the Football team are having an impact on the demand of the last home games of the season. As given in Figure 4.1, a 95% Confidence interval of the Elapsed time of the simulation (in hours) is (38.1109, 38.5509). In other words, the interval of time between Friday at 10. 06a.m and Friday at 10. 33a.m has 0.95 probability of containing the population mean. This might imply a low demand game based on the experience of the athletic office.

Output	Average	Half Width	Minimum Average	Maximum Average
Elapsed Time in hours	38.3309	0,22	35.7314	40.9071

Figure 4.1. Time elapsed of the simulation

Consequently, given that the expected demand is potentially low, we are going to be able to identify if the strategy implemented by the ticket office works well for low demand games, or if it can be improved otherwise. Figure 4.2 shows the number and percentage of rejected calls. Given that only (2.99, 3.717), using a 95% C.I, of the phone calls were rejected (approximately 1%), it appears that the athletic office is overspending in the cost of their resources, as they barely have missing calls. Next, we will take a look at the scheduled utilization of the ticket officers to see if the idea of an overspending in resources is supported. While a low percentage of rejected calls is desired, the economic cost associate with having very low values can be too expensive.

Count	Average	Half Width	Minimum Average	Maximum Average
Number of rejected calls	3.3700	0,38	0.00	9.0000
Perc. rejected calls	0.00989598	0,00	0.00	0.02631579

Figure 4.2. Number and Percentage of rejected calls

Figure 4.3 shows the Scheduled utilization levels for ticket officers by periods. Recall that each period has a different number of ticket officers. As we expected given the low percentage of rejected calls, the scheduled utilization of the resources is also low. Ticket officers for period 1 are busy on average 27.76% of the times, while Officers in period 2 are (32.63, 34.63) % of the time given a 95% confidence interval, and Officers in period 3 are busy 43.2% of the time on average.

Count	Average	Half Width	Minimum Average	Maximum Average
Officer period 1	0.2776	0,00	0.2263	0.3161
Officer period 2	0.3363	0,01	0.2411	0.4197
Officer period 3	0.4320	0,00	0.3974	0.4711

Figure 4.3 Scheduled utilization of the Ticket officers by periods

Given these results, we will expect a low wait time by both phone calls and walk-in Customers. Obviously, as Figure 4.4 shows, online transactions have zero wait time because they are assumed instantaneous operations with unlimited capacity. On the other hand, phone calls show an average time on hold equal to 0.036 minutes or roughly 2 seconds and Walk-in customers an average wait time given by 95% C.I of (0.1245, 0.1445) minutes or (7.47, 8.67) seconds.

Wait Time	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Online transaction	0.00	0,00	0.00	0.00	0.00	0
Phone Call	0.03686822	0,00	0.01508677	0.0974	0.00	6.9[illegible]
Physical Customer	0.1345	0,01	0.06811791	0.2129	0.00	8.6[illegible]

Figure 4.4 Wait time in time by the entities in Minutes

These results show that the strategy implemented by the ticket office, initially created for high demand games, is not working well for low demand ones. Given this, it is the decision of the athletic department to decide if they want to save money by finding alternative strategies. It seems like a cost reduction strategy can be implemented without having a big impact on the percentage of rejected calls and the wait time of the entities.

4.2 Athletic Department response

After having reviewed the results from the simulation, the athletic department has concluded that the current strategy implemented by the ticket athletic office doesn't work well for low demand games. Consequently, they have commissioned me to find an alternative and cost-effective strategy that matches the current low demand with an appropriate daily allocation of ticket officers. The only constraint given is that the new strategy should have a reduction of 20% in the total cost. As Figure 4.5 shows, the total cost for the initial simulated model is 850.5 $, which is a fixed number because it only takes into consideration the 8.1$/ hour that costs to hire a ticket officer. This involves that the new strategy should have a cost no greater than 680$.

Output	Average	Half Width	Minimum Average	Maximum Average
Total Cost	850.50	0,00	850.50	850.50

Figure 4.5. Total cost of the model

Chapter 05: Alternative scenarios

5.1 Introduction to Process Analyzer

Given the new weekly budget of 680$, the goal is to find the allocation of ticket officers that keeps the percentage of rejected calls as well as the wait time for Walk-In customers as low as possible while meeting the budget constraint. This means that, while the athletic department needs to reduce their budget, they still want to keep a high customer service. In the next sections, alternative scenarios will be considered using the *Arena* built-in tool Process Analyzer.

5.2 Aggressive reduction Scenarios

Given that the base scenario was made for high demand games, the first scenario that I contemplated was the reduction of Ticket officers in all three periods. I first created an aggressive scenario as shown Figure 5.1 called *drastic officer reduction* scenario. This scenario is obviously cheaper (413$). It implies a reduction of more than 50% compared to the base scenario cost, but it also involves an increase in the percentage of rejected calls as well as the in Walk-in Customer wait time, as it can be observed in the last tree columns of Figure 5.1. 22.7% of rejected calls and almost 2 minutes on average of wait time per customer are figures that the athletic department is not willing to allow. Consequently, a less aggressive scenario, called *moderate officer reduction* implying the reduction of only 1 officer per period is proposed (as shown in the last row of Figure 5.1). Unfortunately, the response outputs are still far from the desirable levels of the athletic department. The main problem with this scenario is period 3, where the average utilization of the Officer after 100 replications is almost 70%. This is causing the rejected calls to go up as well as the time spent in line by Walk-in customers.

Name	Program File	Reps	Officer 1st period	Officer 2nd period	Officer 3rd period	Officer period 1.ScheduledUtilization	Officer period 2.Scheduled Utilization	Officer period 3.ScheduledUtilization	Perc.rejected calls	Physical Customer. WaitTime	Total Cost
Base scenario	10 : Valles	100	4	3	2	0.278	0.336	0.432	0.010	0.135	850.500
drastic officer reduction	10 : Valles	100	2	1	1	0.550	0.812	0.696	0.227	1.747	413.100
moderate officer reduction	10 : Valles	100	3	2	1	0.370	0.503	0.692	0.200	1.340	486.000

Figure 5.1. Base Case and first 2 scenarios

5.3 Part time hiring Scenario

After having found the problem of the first two alternative scenarios to be in the period 3, an alternative option for this period is considered in this section. As given in Figure 5.1, having only 1 officer for period 3 results in bad customer service, while having 2 might result in an over budget decision, given that period 3 is the longest one and therefore the cost associated with hiring an officer for that period is higher. Consequently, we are going to consider the option of hiring a second part time officer that works from 8-2p.m during the days of period 3. Given that the 2-5p.m shifts have less demand, this alternative can potentially turn out to be satisfactory. Figure 5.2 shows 2 scenarios where a new part time officer has been introduced. Given that both alternatives differ by only 25$, we will analyze the most expensive one because it leads to lower percentage of rejected calls and lower wait time by Customers. As shown in Figure 5.2, this scenario called *Moderate with part time,* leads to an average of 7% of rejected calls as well as a little over 30 seconds wait for Walk-in customers after 100 replications. These results are definitely more in the line with what the athletic department is looking for.

Name	Program File	Reps	Officer 1st period	Officer 2nd period	Officer 3rd period	Officer New Part Time	Officer period 1.ScheduledUtilization	Officer period 2.Scheduled Utilization	Officer period 3.ScheduledUtilization	New Part time Officer.Scheduled Utilization	Perc.rejected calls	Physical Customer. WaitTime	Total Cost
drastic with PartTime-officer	10 : Valles	100	2	1	1	1	0.550	0.812	0.504	0.439	0.093	0.808	614.700
moderate with part tiime	10 : Valles	100	2	2	1	1	0.550	0.507	0.512	0.442	0.070	0.543	639.000

Figure 5.2. Alternative part time scenarios

Even if this alternative seems to deliver more appropriate results for crafting a new strategy for low demand games, an average of 7% of rejected calls can be excessive for a ticket office that has been characterized for their exceptional customer service. As a consequence, I have contemplated 2 other alternatives that despite being over budget, they seem to align better with the principles of the athletic department.

5.4 Over-Budget Scenarios

In order to lower the percentage of rejected calls, two new scenarios have been considered. These scenarios eliminate the part time officers and they simply add 2 officers to the 3rd period. While they both are over budget (704.7$ and 729$), as given in Figure 5.2, they help to reduce both the percentage of rejected calls and the walk-In customer wait time. Also, while the utilization of most of the officers might seem somewhat low, this aligns well with the principles of the athletic department of offering an excellent customer service. Given this, it is now the athletic department decision to select what scenario matches better with their economic and customer service expectations.

Name	Program File	Reps	Officer 1st period	Officer 2nd period	Officer 3rd period	Officer New Part Time	Officer period 1.ScheduledUtilization	Officer period 2.Scheduled Utilization	Officer period 3.ScheduledUtilization	New Part time Officer.Scheduled Utilization	Perc.rejected calls	Physical Customer. WaitTime	Total Cost
over budget-reduction	10 : Valles	100	2	1	2	0	0.550	0.812	0.431	0.000	0.036	0.533	704.700
Over budget-moderate redu	10 : Valles	100	2	2	2	0	0.550	0.507	0.429	0.000	0.012	0.262	729.000

Figure 5.3. Alternative over-budget scenarios

5.5 Comparing the scenarios

So far, we have compared the scenarios based on their average values given 100 replications. However, we haven't been able to conclude what scenario is significantly better than the others. Using the *chart* option of Process Analyzer, and after having specified on what response we want the comparison to be, we can determine what scenario is statistically the best. For instance, given all the possible scenarios, when comparing them amongst percentage of rejected calls, the base scenario is 95% certain to contain the true best scenario in terms of the true (and unknown) expected value of this response. This is given in Figure 5.4, where the Base scenario is in red, meaning that it is significantly better. For a more in-depth analysis of the figures of each scenario, please refer to the table 5.1.

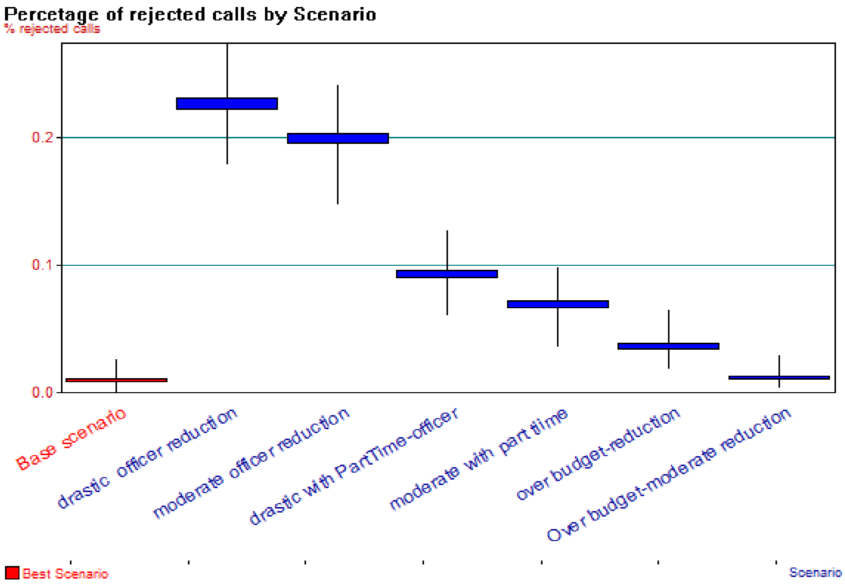


Figure 5.4. Statistical comparison of every scenario by percentage of rejected calls

Scenario	Max	Min	Low	High	Mean	Half width(95%)
Base scenario	0.026316	0	0.008778	0.011014	0.009896	0.001118
drastic officer reduction	0.274627	0.178788	0.223336	0.231211	0.227274	0.003938
moderate officer reduction	0.240964	0.147335	0.195881	0.203769	0.199825	0.003944
drastic with PartTime-officer	0.126888	0.06079	0.090595	0.096081	0.093338	0.002743
moderate with part tiime	0.098462	0.035714	0.067182	0.071977	0.069579	0.002398
over budget-reduction	0.064725	0.01791	0.034404	0.038474	0.036439	0.002035
Over budget-moderate reduction	0.028571	0.00289	0.011007	0.013424	0.012215	0.001209

Table 5.1. Percentage of rejected calls per scenario

When comparing the scenarios by Walk-in customer wait times, similar results are obtained. The base scenario is significantly better than the others as seen in Figure 5.5 and table 5.2

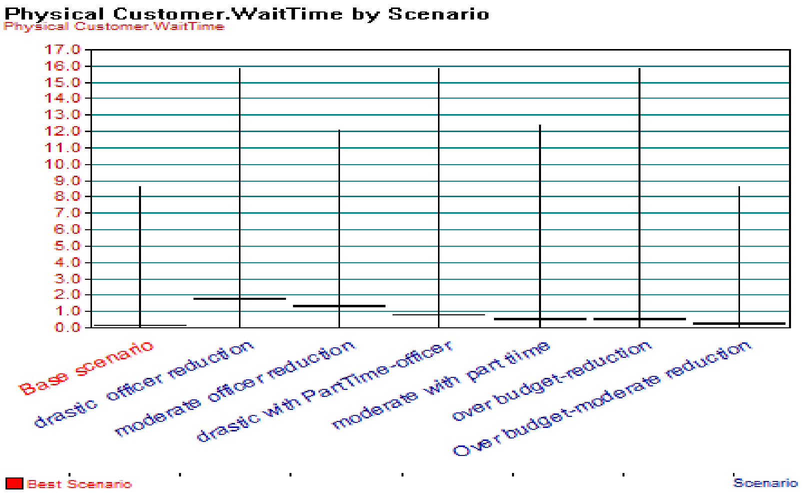


Figure 5.5. Statistical comparison of every scenario by Walk-in Customer Wait Time

Scenatrio	Max	Min	Low	High	Mean	Half width(95%)
Base scenario	8.627529	0	0.128628	0.14042	0.134524	0.005896
drastic officer reduction	15.83379	0	1.714305	1.778801	1.746553	0.03225
moderate officer reduction	12.08288	0	1.313883	1.366056	1.339969	0.02609
drastic with PartTime-officer	15.83379	0	0.786064	0.83029	0.808177	0.02211
moderate with part tiime	12.38831	0	0.526101	0.559339	0.54272	0.01662
over budget-reduction	15.83379	0	0.513461	0.552585	0.533023	0.01956
Over budget-moderate reduction	8.622288	0	0.251354	0.271764	0.261559	0.0102

Table 5.2. Walk-in Customer wait time per scenario

However, given the budget restrictions of the athletic department, every scenario whose cost is above 680$ should be eliminated. Consequently, we are now comparing only those scenarios that satisfy the budget constraints. As shown in Figure 5.6 the scenario that had a total cost of 639$ that included a part time officer (given in Figure 5.2 of section 5.3) is significantly better than the others that satisfy the budget constraints.

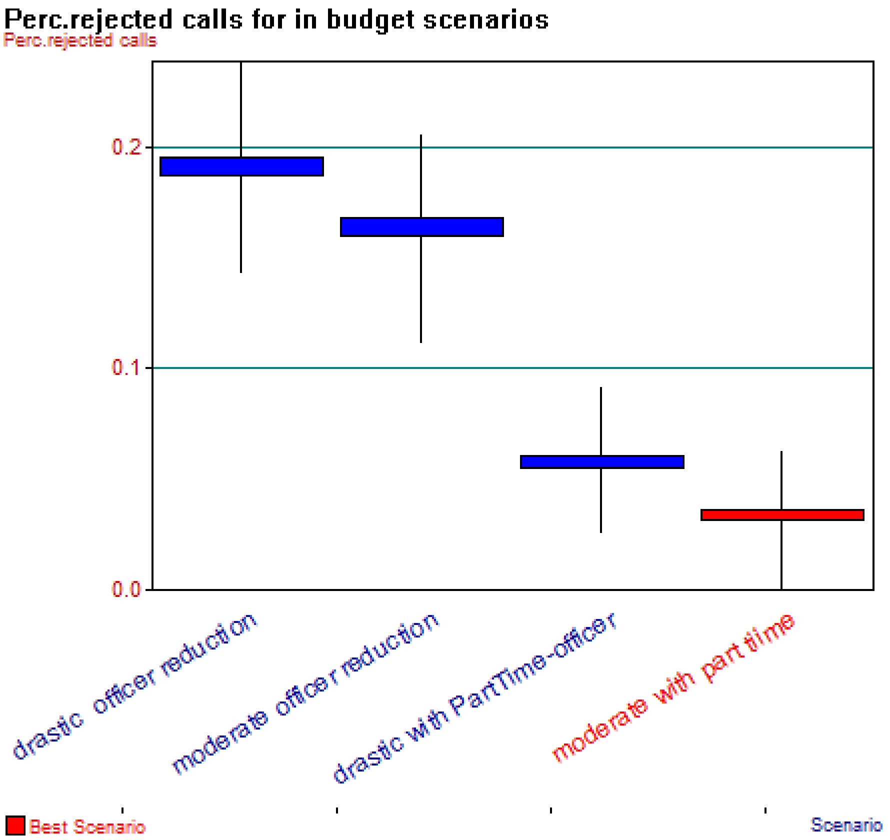


Figure 5.6. Statistical comparison of in-budget scenarios by percentage of rejected calls

Chapter 06: Conclusions and recommendations

This study has simulated the operations of the ticket athletic office of the University of Cincinnati prior to a Saturday Football home game, using *Arena* software. A complete analysis of the results from the original model as well as the analysis of alternatives scenarios have been made. A tradeoff between cost and percentage of rejected calls or Walk-In customer wait time has been observed and it is the decision of the athletic department to decide what responses have higher priority.

Personally, I recommend the athletic department to take the following actions:

1. If the cost needs to be reduced, discard the base model because even if it is significantly better than the other scenarios in terms of rejected calls and wait time for walk-in customers, the elevated cost of this scenario makes it an undesirable strategy for when low-demand games are expected.
2. If it is economically feasible, implement the *over-budget moderate reduction* scenario that had a cost of 729$. Even if it doesn't fulfill the economic requirements, it still implies a 15% cost reduction with the base case, while obtaining, in my opinion, responses values that match the excellent customer service of the athletic department. Table 6.1 shows the similar response values that this strategy gets compared to the base model.

	95% C.I for rejected calls	95% C.I for cusotmers wait time	Cost
Base scenario	(0.00878, 0.011)	(0.01286, 0.1404)	850.5
Over budget-moderate reduction	(0.011,0.013)	(0.25135, 0.2717)	729
moderate with part tiime	(0.067,0.0719)	(0.5261, 0.5593)	639

Table 6.1. Response values for the 3 most recommended scenarios.

3. If the 20% cost reduction should be implemented under any circumstances, implement the *Moderate with part time* that leads to a cost of 639$ and as it was shown in Figure 5.6 it is significantly better than all the scenarios that don't exceed the 680$ limit cost.

It is now the turn of the athletic department to make a final decision and determine how strict they are on their cost reduction constraint.

REFERENCES

-Simulation with Arena sixth edition. W. David Kelton, Randall P. Sadowski, Nancy B. Zupick

-Ticket Athletic Office of the University of Cincinnati. Britany Keller

- UC logo Pictures obtained from: http://www.fbschedules.com