Increasing Efficiency for United Way's Free Tax Campaign

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February 2, 2018

Abstract

United Way of King County's Free Tax Campaign offers free tax return preparation for low-income residents in the greater Seattle area. For many years, United Way has been using the same work flow model, but is now considering switching to a new strategy that could potentially serve more clients. In order to evaluate the which work flow would be more effective, we created Monte Carlo simulations to predict the maximum number of clients a given tax site could serve, given varying numbers of personnel and staff. By analyzing results from both simulations, we concluded it would be beneficial for United Way to change to the proposed new service model. As the Free Tax Campaign grows, the new service model will continue to outperform the previous model. These simulations can also be used to assist in allocating staff across tax sites, in order to maximize the number of people the Free Tax Campaign can serve.

1 Introduction

1.1 United Way's Free Tax Campaign

United Way Worldwide is a nonprofit organization focused on pooling efforts to make changes in local communities. With almost 1,800 offices in 45 countries and territories, United Way is able to identify and resolve issues specific to the communities that they serve [4]. The United Way of King County has a Free Tax Campaign which provides tax return assistance for anyone making under \$62,000 [1] a year. Currently, the Free Tax Campaign organizes and runs tax preparation sites across the metro Seattle area. Their largest site is based at the Seattle Public Library, Central Branch. The Free Tax Campaign is designed to give money back to low-income individuals and families in order to support financial stability, combat homelessness, and promote sustainable lifestyles [5].

For many years, the Free Tax Campaign's client service model has been largely unchanged. Recently they have developed an alternative model in the hopes of serving more clients. Since opening a new site is more costly than changing strategies within their current sites, they would like to consider strategies that will increase the productivity of their established sites. Both strategies are described in Section 2, along with an explanation of how the tax sites operate.

1.2 Problem Objectives

The strategy United Way has been using is prone to bottlenecks during peak times of the tax season. In order to maximize the total number of clients a site can serve, their Burien tax site implemented a new work flow model last year. The site saw huge improvements in the number of clients served. The success at Burien has prompted United Way to consider introducing this new model at their largest location, the Seattle Public Library's Central Branch. However, there are some concerns about implementing a new system at this site. Since Seattle Public Library has the highest client traffic out of all of the tax sites, there are uncertainties as to whether or not the success in Burien can be reproduced on a larger scale.

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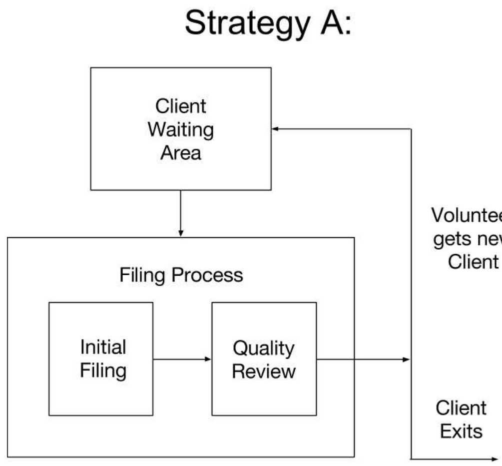
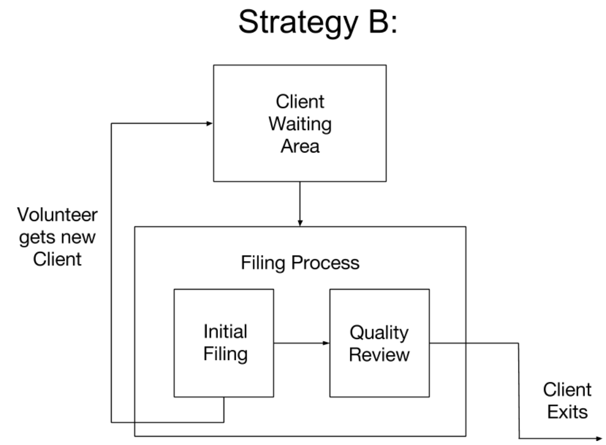
[1] in 2017, this number was updated to \$66,000.



(a) **Strategy A:** The volunteer stays with the client through the quality review process.



(b) **Strategy B:** The client is sent to quality review and the volunteer takes the next client after initial filing.

Figure 1: Flow diagrams of Strategy A and Strategy B.

Jenny Walden, the Program Manager of the Free Tax Campaign, asked us to do a mathematical analysis of their two strategies in order to evaluate which one would be more effective as their program grows. Our goal is to determine which strategy maximizes the number of clients served for varied numbers of volunteers and staff site managers scheduled.

2 Free Tax Campaign Work Flow Strategies

In this section we describe the roles of site managers and volunteers as well as the two strategies we analyzed.

2.1 Volunteers and Site Managers

At tax sites there are two types of staff; volunteers and site managers. The volunteers are members from the community who are trained by United Way before the tax season starts. The role of the volunteer is to assist the client in initially filling out their tax return. Many volunteers come back yearly, and therefore are very efficient in their roles. At a tax site there are typically more volunteers than site managers, since the initial return tends to take longer than the quality review.

Site managers are paid professionals who must do a quality review of every tax return that is processed at a tax site. Since the Free Tax Campaign wants to give the best service to their clients, it is important that every tax return be checked over by a professional before being filed.

2.2 Strategy A

We define the strategy United Way has been using for the last several years as Strategy A. In this strategy, a client is taken from the waiting room by a volunteer to initially fill out the tax return on a first-come first-serve basis. Once the tax return is completed, the volunteer signals for a site manager for quality review. When a site manager is available, they will come over to the volunteer's desk for quality review. During the entire quality review, the volunteer stays with the client and site manager. Once a client's quality review is completed, they are finished with all services. The volunteer is then free to take the next client in the waiting area, and the site manager can do quality review for the next volunteer.

2.3 Strategy B

We define the new strategy adopted by the Burien tax site as Strategy B. The difference from Strategy A to Strategy B is after a client's tax return is completed by the volunteer, the client then leaves the volunteer and enters a queue for a stationary site manager (i.e., sitting at a desk) for quality review. The volunteer is then able to take the next client from the waiting area, rather than staying with the client through the quality review process (as in Strategy A).

3 Mathematical Modeling

In this section we discuss previous research utilizing simulation models and describe some terminology that will be used throughout the paper.

3.1 Literature Review

Simulations are commonly used in queuing theory[2] problems especially when there are unpredictable variables like humans. Wu (1998) uses Monte Carlo simulations[3] to analyze the removal of adverse effects from ethanol from the body, since both ethanol consumption and the removal of its effects from the human body can be modeled as random processes [8]. Kim, Galiza and Ferreira (2013) also apply a simulation model to a movie ticketing booth problem to find the optimal number of booths that should be in service, given different waiting times and arrival times. After running the simulations for a range of different booths and client arrival times, they find that as the number of clients rise, the impact of opening an additional booth becomes more significant [2].

Additionally, Wang et al. (2014) use large-scale Monte Carlo simulations to analyze public transportation patterns and behavior, while accounting for client behavior variances such as balking[4] and reneging[5]. Because the decision to balk or renege can depend on a variety of different environmental factors, these behaviors are also modeled from a random process [6].

The following sections define some terminology that will be used throughout the paper.

3.2 Monte Carlo Simulations and Random Variables

A Monte Carlo simulation uses random numbers generated from some probability distribution to represent a real-world system. We choose to use Monte Carlo simulations due to the unpredictability of service times for every client. Random variables provide a representation of the unpredictability of human behavior. In our problem, random variables are used to represent the possible service time lengths for each client. For example, a client could have a more complicated tax return to fill out than usual, a volunteer could be slower than other volunteers, or a quality review may take longer if there are mistakes in the initial return. By modeling service times as random variables, we can account for the unpredictability of service time lengths in our simulations.

In our simulations, we generate random service times from a range of twenty to thirty minutes for volunteer initial filing service times and ten to twenty minutes for quality review service times. These ranges are based on estimations from the Free Tax Campaign team. The simulations then use these time values to calculate a possible outcome. The resulting outcome from these values are recorded and the process is repeated, often hundreds or thousands of times. By running these simulations many times, we can determine both the most likely outcomes that will occur as well as a wide range of possible outcomes.

Since simulations are repeated many times, they provide a comprehensive view of all of the possible future outcomes of a decision. They also provide a more flexible approach to modeling a real world problem as opposed to an analytical model. Since there are many variables in this model, using an analytical approach (such as a standard k-stage series queuing system) runs the risk of introducing quadratic or cubic terms in the function or the constraints. This would in turn coerce the problem into being non-deterministic polynomial-time complexity (NP), i.e., a problem for which the solution is easy to verify, but the solution itself is very difficult to compute.

[2]Queuing theory is the mathematical study of waiting lines, or queues.
[3]Monte Carlo simulations are discussed in Section 3.2
[4]Balking is when a client decides to not enter the queue at all.
[5]Reneging is when a client leaves a queue before being served.

3.3 Probability Distributions and the Normal Distribution

Data visualization methods allow us to discover patterns or trends within data. When continuous data tends to be centered around a certain value, or within a range of values, without any visible left or right bias, we say that the data follows a normal distribution.

The following are some useful properties of the Normal distribution:

- The mean (average) and the median value are equal.
- 67% of values lie within one standard deviation of the mean.
- 95% of values lie within two standard deviations of the mean.

4 Mathematical Assumptions and Simplifications

Since real-world systems have many variables, we must make some assumptions in order to both feasibly model our simulations and obtain practical results. Below we list the assumptions made in our simulations.

- The number of volunteers and site managers in a given shift are assumed to be constant throughout the entire shift. This means the simulations do not account for breaks or time off within shifts.
- We assume that the time it takes to initially complete a tax form follows a normal distribution with a mean of 25 minutes and a standard deviation of about 1.6 minutes. Furthermore, we assume that the time it takes to complete a quality review also follows a normal distribution with a mean of 15 minutes and a standard deviation of about 1.6 minutes. These estimates of mean and standard deviations are based on data given by United Way. Our justification for choosing the normal distribution is the Central Limit Theorem. In probability theory, the Central Limit Theorem states that the average of a large number of observations from independent random variables will be approximately normally distributed, regardless of the original distribution of the variables. Therefore, in our project, even if service times may not actually be normally distributed, the Central Limit Theorem states that the average values of many service times will follow a Normal distribution. Since we use Monte Carlo simulations, which generate a large number of simulated observations, we can use the Central Limit Theorem as a justification for our model.
- We assume in Strategy B there is a two-minute transition time between initial filing and quality review. By adding a transition time, we consider that clients take some time to get to the quality review location from the volunteer's desk.
- We assume that volunteers are never in an idle state. This means there is always assumed to be a new client in the waiting area when a volunteer becomes available (i.e., infinite client source). This assumption was made because we want to determine the maximum number of clients a tax site can serve with the number of volunteers and site managers scheduled. With more data on how frequently clients arrive at a tax site, this assumption may be changed to better reflect the real world situation.
- We assume that once a client enters the initial waiting area, they do not leave the waiting area or queue if the waiting time becomes too long. With the previous infinite clients source assumption, adding this into the simulation would not change the number of clients in the system significantly. In future analysis, this assumption could be relaxed to better reflect real world behavior.

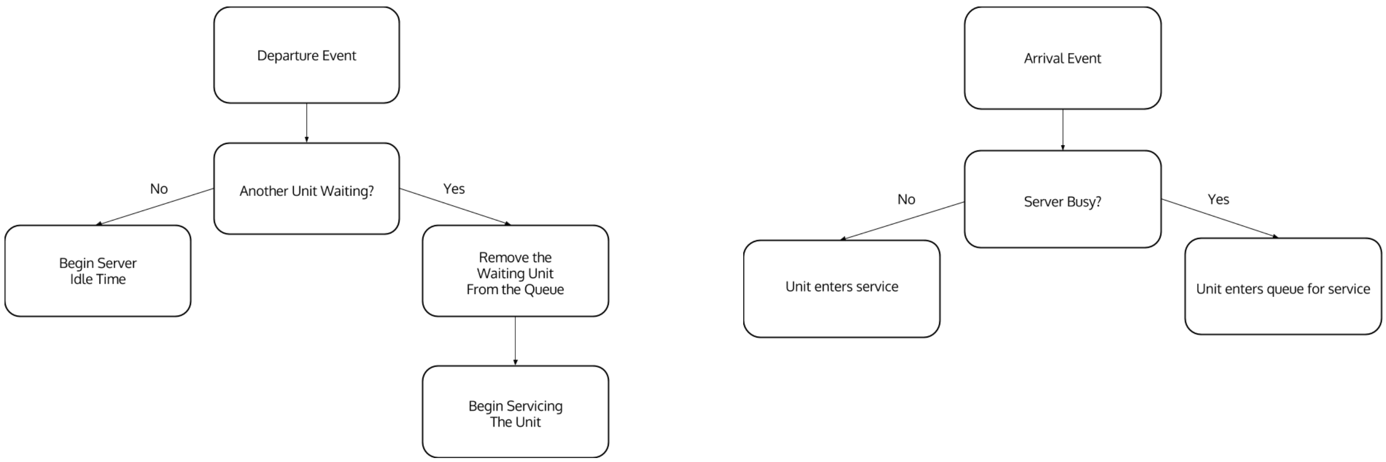
5 Simulations

We create discrete-time Monte Carlo simulations[6] for both Strategy A and Strategy B work flows to simulate what happens in a tax site and measure the number of clients whose tax returns we completed in a given shift. By using simulations, we are able to account for unpredictability of a real-world system with real people.

Both simulations take the following inputs:

- Total Time: The shift time a user wants to simulate (in minutes).
- Total Volunteers: The number of volunteers scheduled for the shift to be simulated.
- Total Site Managers: The number of site managers scheduled for the shift to be simulated.

[6]For more information about discrete-time simulations we recommend [1]



(a) **Departure Event:** A departure event happens when a client's service is completed and they leave the server. The server is now free to take another client in line or become idle.

(b) **Arrival Event:** An arrival event happens when a client arrives at a service. If there is an idle server, then the client can go to that server and immediately begin the service, otherwise the client will join the queue.

Figure 2: Flow diagrams of arrival and departure processes. At every event there is an arrival and/or a departure in a queueing simulation. These flows show what has to be done at each of these event types.

Both simulations use the same generators to obtain random numbers. We use a `Python` command that generates random numbers based on a Normal distribution that follows a mean and standard deviation given by the user. Both simulations use the same random number generator in order to remain consistent in how the service times are generated.

In our simulations, the system is a tax site with some given number of volunteers and site managers and the state describes the system at a given point in time. In our simulation the state is the status of the site managers, how far along the site managers and volunteers are in a service, and the length of the queue for the site managers. An event is something that changes the state of the system. In a queuing system we have departure and arrival events, as diagrammed in Figure 2. A departure event happens when a client departs a service after completion as illustrated in Figure 2a. After the client leaves, the server checks if there is another client waiting in the queue. If there is a client then they immediately begin service for the next client, otherwise the server enters an idle state where they are not serving any clients. An arrival event is when a client arrives at a service as illustrated in Figure 2b. In this event the client checks if a server is available. If a server is available then the client begins the service with the available server, otherwise the client enters into the queue.

The simulations for Strategy A and Strategy B simulate clients being served over a shift time. The simulation measures time by having a simulation clock time that starts at zero from the start and is increased through the simulation. When the clock time reaches the time of a scheduled event, the state of the system is updated to represent the scheduled event. Once the clock time reaches the given shift time the simulation is finished, and outputs the total number of clients served (i.e., the clients' tax returns were completed). By running these simulations many times we can compute statistical measures to see how many clients a strategy serves on average. We can then use this information to determine which strategy serves more clients overall.

5.1 Strategy A Simulation

In the Strategy A system, the possible events are: (1) an arrival event at the site manager, (2) a departure from site manager quality review, or (3) initiating a new client when the volunteer or site manager is available.

(1) When a volunteer completes a tax return, there is an arrival event at the site manager. In the real world, the volunteer flags down a site manager for quality review. In the simulation, if a site manager is available (in an idle state) then the volunteer and client enter the site manager service. A random service time is generated by

the random number generator to schedule when the site manager quality review will be complete. If all the site managers are busy then, in the simulation, we have the volunteer stored in a queue that keeps track of which volunteer flagged down a site manager first. Note that we do not have a departure event from the volunteer since the volunteer stays with the client through the quality review process.

(2) The other event is a client's quality review being completed. This creates two departure events simultaneously: one from the volunteer and one from the site manager. At this time, the client is counted as a completed client and leaves the system.

(3) After a departure, both the site manager and volunteer that were with this client are no longer busy so both the volunteer and site manager process an arrival event. Since we have assumed there is always someone in the waiting room, the volunteer immediately takes the next client and a random service time is generated. The site manager also processes an arrival event. If there is a volunteer and client in the queue, the site manager begins the quality review with the first volunteer and client in the queue by generating a random service time. If there is no one in the queue, the site manager is marked idle.

5.2 Strategy B Simulation

In the Strategy B system, we have two possible events: (1a.) a departure from volunteer tax return completion which leads to (1b.) an arrival at the site manager or (2) a departure from site manager quality review.

(1) When a volunteer completes a tax return, the client then leaves the volunteer for their quality review.

   a. The client has left the volunteer so the volunteer is available. This is a departure event. The volunteer takes the next client in the waiting room to begin the next client's tax return because we assume there is an infinite client source in the waiting room. In the simulation a random service time is generated to schedule when this tax return will be complete. Two minutes are also added to the generated service time to account for client transition time to quality review.

   b. When the client that left the volunteer goes to the site manager for quality review there is an arrival event at the quality review service. If a site manager is available, the client immediately begins the quality review service by a random service time being generated to schedule when the quality review will be complete. Otherwise, if no site manager is available, the client enters the site manager queue.

(2) When a site manager completes a quality review, the client has now completed all the services and is counted as a completed client. If there are clients in the queue, the site manager takes the next client and a random service time is generated. Otherwise, the site manager is marked as idle.

5.3 Software

All the simulations were written in `Sage`, an open-source mathematics software that builds on top of existing open-source packages [3]. By using `Sage`, United Way can use the simulation model for further exploration. Additionally, it is not necessary to download any software on a computer to use `Sage`. Instead, anyone can use the SageMathCloud at `https://sagemathcloud.com` to use the simulations. The ability to access our code online allowed us to easily share our simulations with United Way for further use.

6 Results and Analysis

We ran simulations for Strategy A and Strategy B 10,000 times each for seven hour shift times. The median number of completed clients produced under each of the simulations, given various number of volunteers and site managers, are recorded in Tables 1 and 2. In the Appendix, Tables 3 and 4 have results for a larger range of volunteers and site managers.

When there are more site managers assigned to a site, Strategy B tends to outperform Strategy A. Note that Strategy B always has about the same (within one) or more completed clients than Strategy A. In both Strategy A and Strategy B, for one or two site managers there are about the same median number of completed clients, regardless of the number of volunteers in Tables 1 and 2. However, when adding a third site manager, we find a larger increase in the number of completed clients for Strategy B than Strategy A for the lower number of volunteers. We continue to see this trend when increasing the number of site managers. Extended tables in the appendix show that Strategy B continues to outperform Strategy A after adding three site managers.

Strategy A

Site Managers \ Volunteers	10	11	12	13	14	15
1	26	26	26	26	26	26
2	52	52	52	52	52	52
3	78	78	78	79	79	79
4	95	101	104	104	104	104
5	98	107	115	123	128	130

Table 1: The median number of clients completed for a shift time of seven hours, with the number of volunteers and site managers indicated by the row and column of table for 10,000 iterations of the Strategy A simulation.

Strategy B

Site Managers \ Volunteers	10	11	12	13	14	15
1	26	26	26	26	26	26
2	52	52	52	52	52	52
3	78	78	78	78	78	78
4	103	103	103	103	103	103
5	129	129	129	129	129	129

Table 2: The median number of clients completed for a shift time of seven hours with the number of volunteers and site managers, indicated by the row and column of table for 10,000 iterations of the Strategy B simulation.

Another interesting observation is that when there are many more volunteers than site managers, scheduling an additional volunteer to a shift does not tend to increase the number of completed clients significantly. In contrast, we see that scheduling an additional site manager to a shift does tend to result in a significant increase in number of completed tax returns in the ranges shown in Tables 1 and 2. An explanation for this is that a marginal increase in the number of volunteers (i.e., the added benefit of adding one more volunteer to a shift) is not as great as a marginal increase in the number of site managers. In economic terms, the marginal product of labor for volunteers (the additional change in output from adding one more unit of labor) is lower than the marginal product for site managers.

6.1 Proposed Future Work

With more data of the real-world system, future work may be done to build on the simulations for the United Way's Free Tax Campaign as well as adapt to more service models.

- Currently our simulations do not measure the amount of time that a client is in the system. Since we are assuming that there is an unlimited number of clients in the initial waiting area, we do not have a way to determine how long a client is at the site from arrival to completion of services. With more data about how the clients arrive, an arrival distribution may be incorporated to determine how much time clients spend at the tax site.
- Our simulations do not measure shift changes. A site may have changes in the number of volunteers and site managers throughout a shift due to breaks. In future work implementing breaks we could give a more accurate estimation of how many clients a site can serve in any given shift.
- The number of completed clients given by simulations may not exactly represent capacity for a tax site with a given number of volunteers and site managers. Since the service time distributions were based on observations, they may not be as accurate as measured data. After comparing the simulation outputs to the real world systems and future data, these simulations may be updated to get more exact values for the capacity of a tax site.

6.2 Conclusions

United Way's Free Tax Campaign has been growing over the last several years. Based on our results from the simulations, we recommend that United Way change to Strategy B for sites that will have at least three site managers. In particular, it would be beneficial to implement Strategy B because it is always better or about equal to Strategy A when comparing the number of completed clients. From Tables 3 and 4, we see that the differences between Strategy A and Strategy B continue to grow as we add more managers and volunteers. Because United Way predicts growth for the Free Tax Campaign in the future, as the tax sites grow, Strategy B will outperform Strategy A.

United Way's Free Tax Campaign can also use this data to determine how many site managers and volunteers they actually need at each site. In our simulations, increasing the number of volunteers most of the time did not significantly increase the number of clients served. We can see that it may not always be beneficial to add volunteers. Similarly, in some cases shown in Tables 3 and 4 there is no completed client gain when adding another site manager. By using this data, the Free Tax Campaign team can determine how to distribute volunteers and site managers per tax site in order to optimize how many clients can be served through the whole system.

By taking these results into the decision making processes the Free Tax Campaign can maximize their capacity to serve clients by determining which type of server they need to add based on which strategy is used at that site. As more data is recorded, these simulations can be further updated to continue to help the Free Tax Campaign team in their decision making process. Additionally to helping the Free Tax Campaign, these simulations can be easily adjusted to fit similar work flow models for all sorts of service organizations.

7 Acknowledgments

We would like to thank Jenny Walden, MSW, program manager of the Free Tax Campaign at the United Way of King County for taking the time to come up with this project and for answering all our questions about the program. We also would like to thank Professor Sara Billey, University of Washington-Seattle Department of Mathematics, for her passion for the Discrete Modeling course and tirelessly giving great feedback, ideas, and guidance for our projects. Finally thank you to Austin Tran, Alan and the Little Sheep Mongolian Hot Pot team for giving us great feedback on our project drafts.

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8 Appendix

8.1 Extended Strategy Tables

These are an extended versions of Tables 1 and 2. In these tables we have the median completed clients for 1,000 runs through the simulation for the various volunteers and site managers.

Strategy A

Volunteers

	3	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	27	26
2	30	39	47	52	52	52	52	52	52	52	52	52	52	52	52	53	52	52
3	30	40	50	59	67	74	78	78	78	79	79	79	79	78	78	78	79	78
4	30	40	50	60	69	79	87	95	101	104	104	104	104	104	104	104	104	105
5	30	40	50	60	70	79	89	98	107	115	123	128	130	130	130	130	130	130
6	30	40	50	60	70	80	90	99	109	118	127	135	143	150	154	156	156	156
7	30	40	50	60	70	80	90	100	109	119	128	137	147	155	164	171	177	181
8	30	40	50	60	70	80	90	100	110	119	129	139	148	157	166	175	184	192
9	30	40	50	60	70	80	90	100	110	120	129	139	149	158	168	177	186	195
10	30	40	50	60	70	80	90	100	110	120	130	139	149	159	168	178	187	197

Table 3: Table of the median completed clients for 1,000 runs through Strategy A simulation with shift time of seven hours for indicated volunteers and site managers. The average variance of these results was 1.51.

Strategy B

Volunteers

	3	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26
2	43	51	52	52	52	52	52	52	52	52	52	52	52	52	52	52	52	52
3	43	58	72	77	77	78	77	78	78	78	78	78	78	78	78	78	78	78
4	43	58	72	87	100	103	103	103	103	103	103	103	103	103	103	103	104	104
5	43	58	72	87	101	116	128	129	129	129	129	129	129	129	129	129	129	129
6	43	58	72	87	101	116	130	144	154	155	155	155	155	155	155	155	155	155
7	43	58	72	87	101	116	130	145	159	173	180	181	181	181	181	181	181	181
8	43	58	72	87	101	116	130	145	159	174	188	201	206	206	206	207	206	206
9	43	58	72	87	101	116	130	145	159	174	188	203	217	229	232	232	232	232
10	43	58	72	87	101	116	130	145	159	174	188	203	217	231	245	256	257	258

Table 4: Table of the median completed clients for 1,000 runs through Strategy B simulation with shift time of seven hours for indicated volunteers and site managers.The average variance of these results was 2.64.

Differences Between Strategy A and Strategy B

Volunteers

	3	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0
2	13	12	5	0	0	0	0	0	0	0	0	0	0	-1	0	-1	0	0
3	13	18	22	18	10	4	-1	0	0	0	-1	-1	-1	-1	0	0	-1	0
4	13	18	22	27	31	24	16	8	2	-1	-1	-1	-1	-1	-1	-1	0	-1
5	13	18	22	27	31	36	39	31	22	14	6	1	-1	-1	-1	-1	-1	-1
6	13	18	22	27	31	36	40	45	45	37	28	19	12	5	1	-1	-1	-1
7	13	18	22	27	31	36	40	45	50	54	52	43	34	26	17	10	4	0
8	13	18	22	27	31	36	40	45	49	55	59	62	58	49	40	32	22	14
9	13	18	22	27	31	36	40	45	49	54	59	64	68	71	64	55	46	37
10	13	18	22	27	31	36	40	45	49	54	58	64	68	72	77	78	70	61
11	13	18	22	27	31	36	40	45	49	54	58	63	67	73	77	81	86	84

Table 5: This table shows the differences between the medians of the number of completed customers for 1,000 runs through both Strategy A simulation and Strategy B simulation with respective volunteers and site managers. We subtracted the median of Strategy A from median of Strategy B. If an entry is 0 then there is no difference. If the entry is positive then Strategy B has a median completed clients greater by that amount. If the entry is negative then Strategy A has a greater median by the absolute value of that value. For example for 17 volunteers and 2 site managers the value is -1. Then we say there is a median of one more client serves by Strategy A than Strategy B for 17 volunteers and 2 site managers.