Harry's Drive-Through Restaurant

CS 5420
Project Documentation

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Abstract

This research oriented project focuses on the case study found on page 158 in chapter 5 of the course text, Harry’s Drive-through Restaurant.

The owner of the restaurant has provided information related to the general activities of the restaurant, such as customer inter-arrival rates, customer group sizes, employee service times, etc… The owner requests assistance analyzing the activity of the business in order to estimate ways to improve the efficiency and effectiveness of the business. The primary concern for the owner is to maximize the number of customers served during rush periods. Secondary considerations are the time customers spend in the system, customer balks, and customer seating.

We make use of discrete event simulation to model and validate the restaurant’s current activities, or baseline behavior.

Using information provided by the owner of the restaurant we developed an input-output model, which was the basis for the base model. We examined the performance of the base model and noticed that the front counter servers were particularly underutilized, while the kitchen servers were overwhelmed with orders. This lead to the development of the intermediate model, which essentially moves one of the front counter employees into the kitchen to help process orders.

Using Minitab, we conducted a two sample hypothesis tests, or t-test, comparing the mean total customer exits of the base and intermediate models. These parameter values were found to be statistically significant at the 5% level.

We then took this intermediate model and imported it into ProModel companion software and model optimizer called SimRunner. SimRunner helped us identify four candidate advanced models, whose parameter values we took and ran simulations for these models in ProModel.

We also ran two sample hypothesis tests for each of the advanced models compared the mean total customer exits against the intermediate model. Each was found to be statistically significant at the 5% level, which suggests that each model is an improvement over the intermediate and base models.

We then briefly discussed some of the strengths and weaknesses of a more statistical and quantitative approach toward discrete simulation analysis.

We also addressed some of the short shortcomings of our analysis and considerations for future analysis, such as studying more deeply the differences in walk-in and drive-through customer activity.

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1. Introduction

We have been retained by the owner of Harry's Drive-through Restaurant, found on page 158 of Chapter 5 of the course text, to implement a discrete event simulation of the restaurant's operations and activities.

The owner of the restaurant has provided information related to the general activities of the restaurant. The owner requests assistance analyzing the activity of the business in order to estimate ways to improve the efficiency and effectiveness of the business.

The primary concern for the owner is to maximize the number of customers served during rush periods. Secondary considerations are the time customers spend in the system, customer balks, and customer seating.

We make use of discrete event simulation to model and validate the restaurant's current activities. We use this model to search for immediate improvements to the restaurant's operations that the owner could potentially implement with minimal adjustment to operations, such as identifying the current bottle-necks and underutilization of resources.

We make use of the discrete event modeling software ProModel and its complementary and adjunct product SimRunner. SimRunner facilitates searching for optimized simulation models.

Using ProModel and SimRunner, we will then attempt to identify more advanced discrete optimization models that the restaurant can reasonably adopt and implement to improve its performance of maximum customer throughput during peak periods.

These candidate models will then be simulated and replicated in ProModel to generate mean total customer processing values that can be further analyzed with hypothesis testing, that is with two sample t-tests. Statistical significance is not necessarily practical significance, so any proposed model will need to be reviewed and approved by the owner of the restaurant.

Ample tables and graphs will be employed in this report to facilitate the reader's understanding of the report details.

All work was completed with the use of the following software:

- ProModel
- SimRunner
- Matlab
- Minitab
- Microsoft Word
- Microsoft Excel

2. Related work

There have been many papers written about the use of simulation to analyze the operations in the food service industry in general, and the fast-food industry in particular. Some such as Swart and Donno [5] predate the use of inexpensive computers and pervasive software easily obtained today.

Many, if not most of these articles employ the use of software, such as the use of Arena in [1], customized C++ programming in [2], WITNESS in [3], ProModel in [4], which was used for this report.
Many authors, such as [1] focus on the use of queuing theory to implement their analysis, and others such as [2, 3, 5] employ varying levels of elementary statistics. Fewer authors, it appears, employ statistical analysis to a broader and deeper extent, and although [4] is an exception, their use of more advanced statistical tools seems to be impeded by the modest length of their article.

We hope to make a small contribution toward emphasizing the beneficial role of statistical analysis in the use of discrete event simulation. Just as discrete event simulation can help analysts to model and analyze complex systems, we believe that statistical analysis can help to better understand the stochastic nature of such systems.

3. Using Discrete Event Simulation for Fast Food Restaurants

3.1. Overview of discrete event simulation

Simulation is the organized method of codifying and estimating the behavior of complex systems, with discrete event simulation being a subset of this process. Simulation may involve continuous systems, such as time or based on the real number line, where as discrete event simulation breaks up activities to discrete units, or time intervals, and employs stochastic methods to mimic random behavior [6].

3.2. Why discrete event simulation

Discrete event simulation is a useful tool, because it facilitates a deeper understanding of complex systems, by viewing and studying a system as a whole, as opposed to viewing parts of a system separately.

Due to the speed at which model changes can be made, discrete event simulation facilitates “what if” mentality and encourages the exploration of alternative models.

Discrete event simulation is relatively inexpensive when compared to approaches such as trial-and-error.

3.3. Problems encounter when implementing discrete event simulation

A problem encountered in a more research oriented project, such as this report, is that you may have fewer references upon which to compare your model and obtain feedback.

When modeling a physical location we could speak to the owner and employees and request feedback for a models practicality. This is not possible with a more research oriented report, although it may be possible to consult industry standards and benchmarks to help alleviate this information deficit.

3.4. Available solutions

There are many approaches to simulating and analyzing a fast-food restaurant. Discrete event simulation is one, a more pure statistical analysis is another, and industrial engineers might suggest time-and-motion studies along with queuing theory analysis. Operations research analyst might optimization techniques.

We believe that discrete event simulation provides a comprehensive analytical solution, whereby time-in-motion, optimization, statistical, and other can all play a role in understanding complex systems.

3.5. General Discussion

We believe that we can contribute something, however small, to discrete event simulation by taking an approach that is perhaps more statistical in nature than other papers.

We think that this approach, when not abused, can garner increased confidence from the client, in the analyst's work by providing the client objective, defensible, quantitative analysis.

4. Project Description

4.1. Overview

We employ discrete event simulation to study the operations of Harry's Drive-Through Restaurant. Using information provided by the owner of the restaurant we will develop base, intermediate, and advanced models to facilitate operational improvements to the restaurant.

4.2. Methods

We will employ discrete event simulation, optimization, and statistical hypothesis testing to facilitate finding ways to improve the operations of Harry's Drive-Through Restaurant.

4.3. Phases

We will initially gather input information from the owner to develop input-output models. We'll then validate our understanding of the system with a base model.

The base model will serve as a foundation for an intermediate model. The intermediate model will serve as a guide to finding optimal models with the use of ProModel and SimRunner software products.

4.4. Limits and Strengths

Discrete event simulation and statistics, when used properly, are powerful and insightful tools to examine and understand complex systems. The help uncover patterns in activity and data that might be overlooked by human analysts.

These tools come at a cost of learning how to use them properly, and should be used in conjunction with the valuable feed back from a subject matter expert, when one is available.

Discrete event simulation and statistical methodologies are not a replacement for contemplation, good judgment, and valuable input from subject matter experts. On the contrary, they enhance and facilitate such activities by handling the heavy burden of running simulations and doing tedious statistical calculation, so that the analyst can focus on understanding the systems under consideration and communicating their insights to the client and other users of the system under consideration.

5. Project Analytics

5.1. Introduction and Overview

As stated previously, Harry’s restaurant would like to improve its ability to serve customers during peak periods of customer activity.

At this point, the base model has been validated with the information provided by Harry’s restaurant. An intermediate model has been quickly developed and is available for the restaurant’s immediate implementation.

The client, Harry’s restaurant, found the intermediate model intriguing and appealing, but desires to see additional advanced models of the restaurant in an attempt to increase the potential for additional customers’ served.

In order to keep the potential models to a reasonable number to consider, we used SimRunner optimization software to generate 12 potential models, and then limited the number of advanced models to four.

Harry’s base model provided one inter-arrival rate for walk-in and drive-through customers, as shown in Table 1 below. Inter-arrival rates allow for some sensitivity analysis, we then incremented the rate by one unit to simulate a slightly shorter period between customer arrivals. The four models were selected to be the optimized models for each combination of inter-arrival rates.

The following is the simulation layout from the ProModel simulation software.

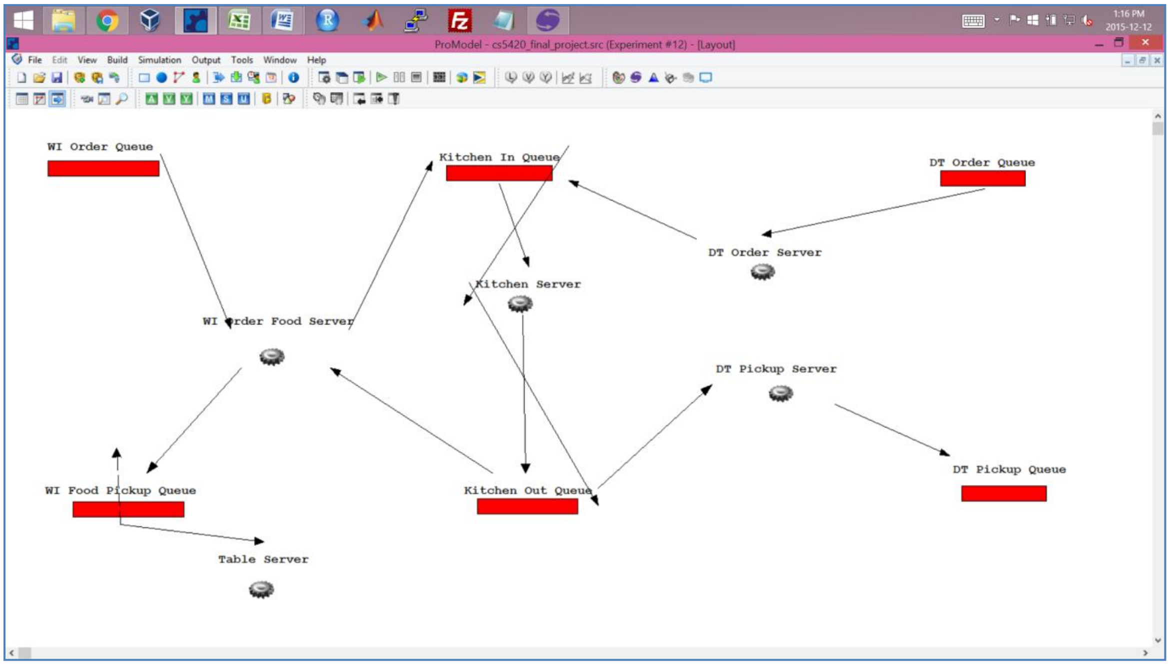


Figure 1 ProModel layout of Harry's Drive-Through Restaurant

This layout will be used in all of the models in this analysis, because although certain parameters of the model may change, such as additional cooks in the kitchen, or a change in an inter-arrival rate, the basic layout, at least for the simulation, remains the same.

For example, to model a kitchen with four instead of three cooks, it is only necessary to increase the capacity of the kitchen server, it is not necessary to add additional servers in the simulation model.

5.1.1. Input-Output Model

The input-output model for this report is shown in Table 1 below.

Table 1 Input-Output Model

CS 5420 Project – Harry's Drive-Through Restaurant	
Input Model	
Walk-in inter-arrival rate	Exponential (4 minutes)
Walk-in eating time	Normal (mean = 15 min, sd = 2 min)
Drive-through inter-arrival rate	Exponential (6 minutes)
Time to take customer orders	Uniform (.5 minutes, 1.2 minutes)
Time to cook orders	Normal (mean = 8.2 min, sd = 1.2 min)
Output Model	
Total number of customers processed during peak periods (primary interest)	
Mean total time in system (secondary interest)	
Customer balks (secondary interest)	
Mean table utilization rate (secondary interest)	

The input and output values will be reported for each model, even though some parameters, such as the mean service time to take an order will remain the same.

Some input parameter values were eventually left at their current values, because they were not shown to be influential under any scenario. The mean service time for taking customers orders was one such parameter that will remain unchanged throughout the analysis.

5.2. Base Model

5.2.1. Introduction

The base model has the default values provided by Harry's restaurant. The input-output values for this model are in Table 2 below.

Table 2 Base Model Values

Base Model	
Input Model Values	
Dine-in inter-arrival rate	Exponential (4 min)
Dine-in eating time	Normal (mean = 15 min, sd = 2 min)
Drive-through inter-arrival rate	Exponential (6 min)
Time to take customer order	Uniform (.5 min, 1.2 min)
Time to cook order	Normal (mean = 8.2 min sd = 1.2
Total Cooks	2
Walk-in Service Employees	2
Output Model Values	
Mean total customers processed	28.62
Mean total time in system	33.18
Mean customer balks	2.43
Mean table utilization rate	3.69

Output values and input values that differ between models or between the base model and the current model will also be highlighted to draw attention to these values.

5.2.2. Analysis

The values in the table represent the values in the table represent the current activity at the restaurant. Figure 2 below displays the activity level in the base model's simulation for various queues and servers in the current system.

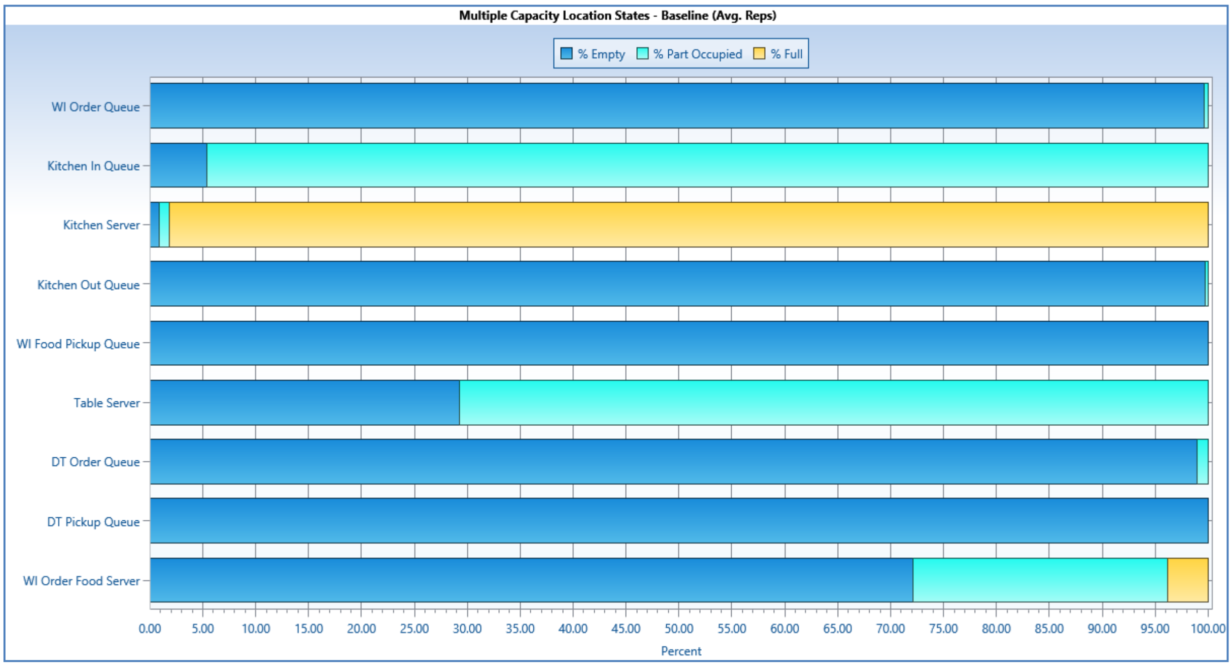


Figure 2 Various Queue and Server Activity for Base Model

It appears that the kitchen is an area of congestion, with 98% utilization, while the two employees serving the walk-in customers in the WI_Order_Food_Server are relatively idle. The WI_Order_Food_Server is a single server with the capacity of two, representing the two employees that are taking orders from customers and dispensing completed orders to customers. These areas will be investigated in the intermediate model. Distribution information is shown in Figure 3.

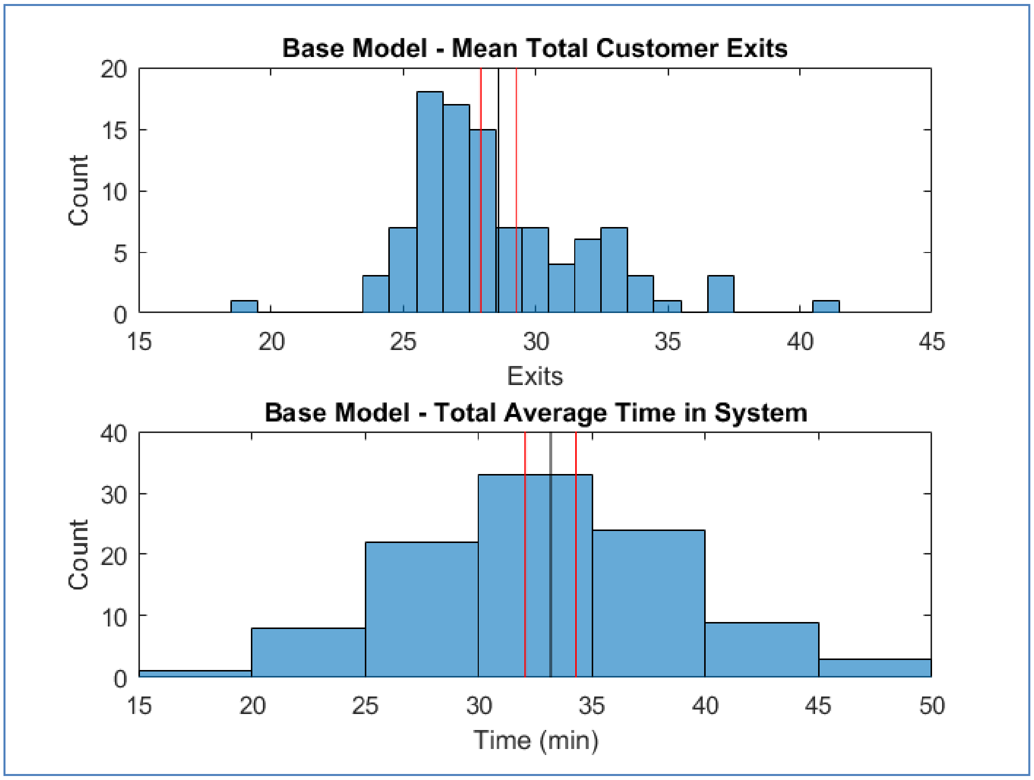


Figure 3 Base Model Histograms for Customer Exits and Total Time in System

Figure 3 provides a visual display of the distribution of mean total customer exits and the mean time in the system for 100 replications of the base model in ProModel. The customer exits distribution is a bit right skewed, but with a sample size of 100, this slight skewness shouldn't cause a problem with any inferences on customer mean exits.

Table 3 provides the information for the confidence intervals in Figure 3.

Table 3 Base Model 95% CI Values for Exits and Wait Time

Base Model					
Item	Sample Size	Std Dev	Lower 95% CI	Mean	Upper 95% CI
Mean total customers processed	100	3.41	27.95	28.62	29.28
Mean total time in system	100	5.74	29.29	33.18	34.30

Tables similar to Table 3 are available in Appendix C for the intermediate and advanced models.

5.2.3. Conclusion

The base model will serve as a benchmark from which additional models will be measured. The kitchen should be investigated as the primary bottle-neck and the two walk-in customer servers as a source of excess capacity.

5.3. Intermediate Model

5.3.1. Introduction

The base model exposed the kitchen as the primary bottle-neck in the restaurant, while the two employees serving walk-in customers were relatively idle.

The intermediate model proposes to move one employee from the front walk-in counter back to the kitchen to help process orders. The input-output values for this model are in Table 3 below.

Table 4 Intermediate Model Values

Intermediate Model	
Input Model Values	
Dine-in inter-arrival rate	Exponential (4 min)
Dine-in eating time	Normal (mean = 15 min, sd = 2 min)
Drive-through inter-arrival rate	Exponential (6 min)
Time to take customer order	Uniform (.5 min, 1.2 min)
Time to cook order	Normal (mean = 8.2 min sd = 1.2
Total Cooks	3
Walk-in Service Employees	1
Output Model Values	
Mean total customers processed	38.22
Mean total time in system	23.86
Mean customer balks	0.19
Mean table utilization rate	5.52

As mentioned previously, items of interest have been highlighted. The mean customer balk rate and the mean table utilization rates are were of initial interest to the customer, their values under simulation, having not shown to be a significant factor in the restaurant's operations. Thus, we will not highlight them going forward, so as not to give them more importance than they deserve.

5.3.2. Analysis

We have moved one employee from the front counter back into the kitchen to help process orders. The most important values from the restaurant's point of view are that with the same total number of employees, on average, the restaurant was able to process 34% additional customers. Simultaneously, the restaurant was able to reduce the total time in the system by customers by 28%

Figure 3 below shows the effect on the kitchen server utilization for the intermediate model. The top horizontal bar is the capacity information for the kitchen server for the base model, while the middle horizontal bar represents the kitchen server results for the intermediate model.

The front counter server, which only has one employee, has but a single entry on the bottom, because this chart presents multi-capacity locations.

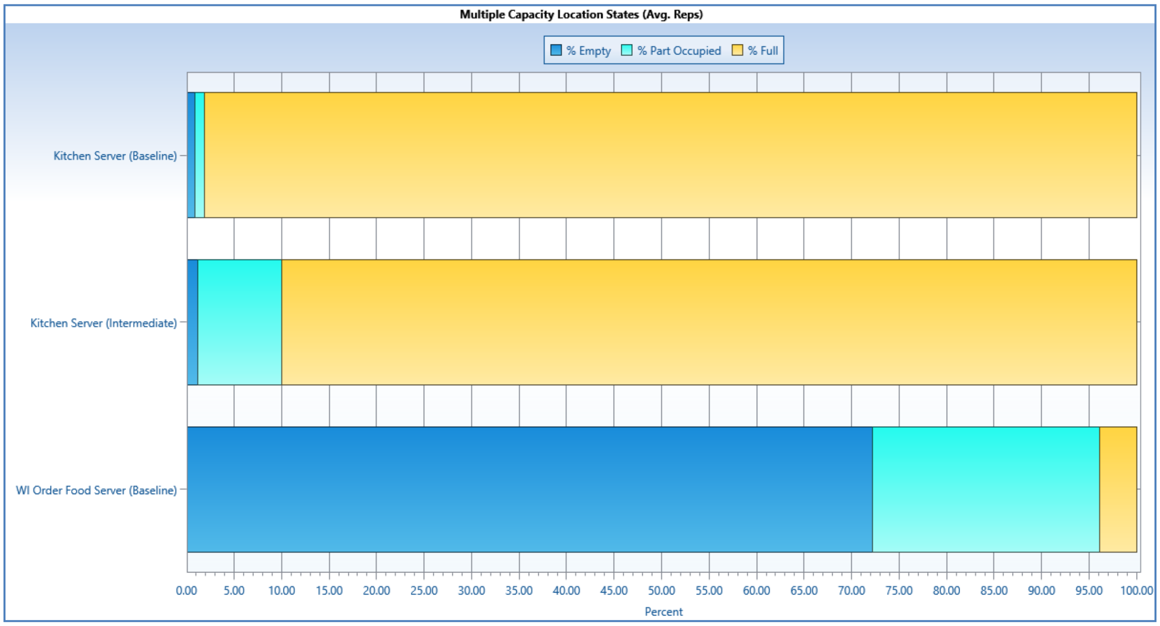


Figure 4 Selected Multi-capacity Locations for Intermediated Model

Figure 4 below provides the utilization rate for the now single capacity location called WI_Order_Food_Server.

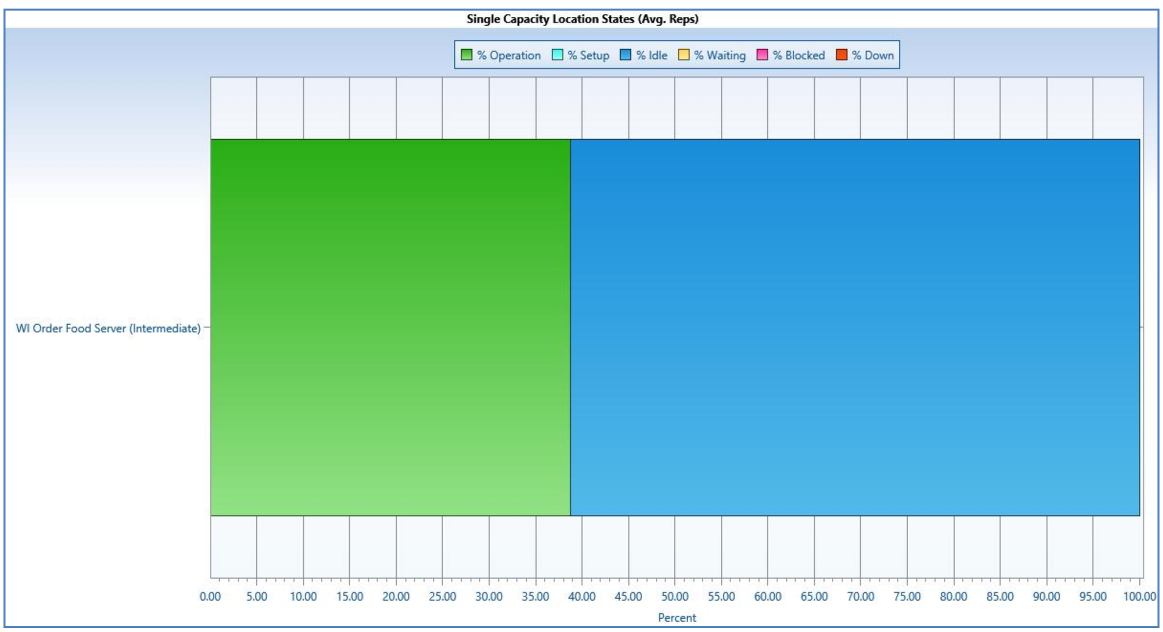


Figure 5 Utilization for Single Capacity WI_Order_Food_Server

The utilization rate for the kitchen server is now down to 95%, which is still too high, but an improvement. The utilization rate for the front counter was 16% in the base model, but has increased to 39% in the intermediate model. These and other values are available in Appendix B. Figure 6 below has the plotted distribution values for the intermediate model's mean total customer exits and the mean total wait time for customers, similar to Figure 3 above.

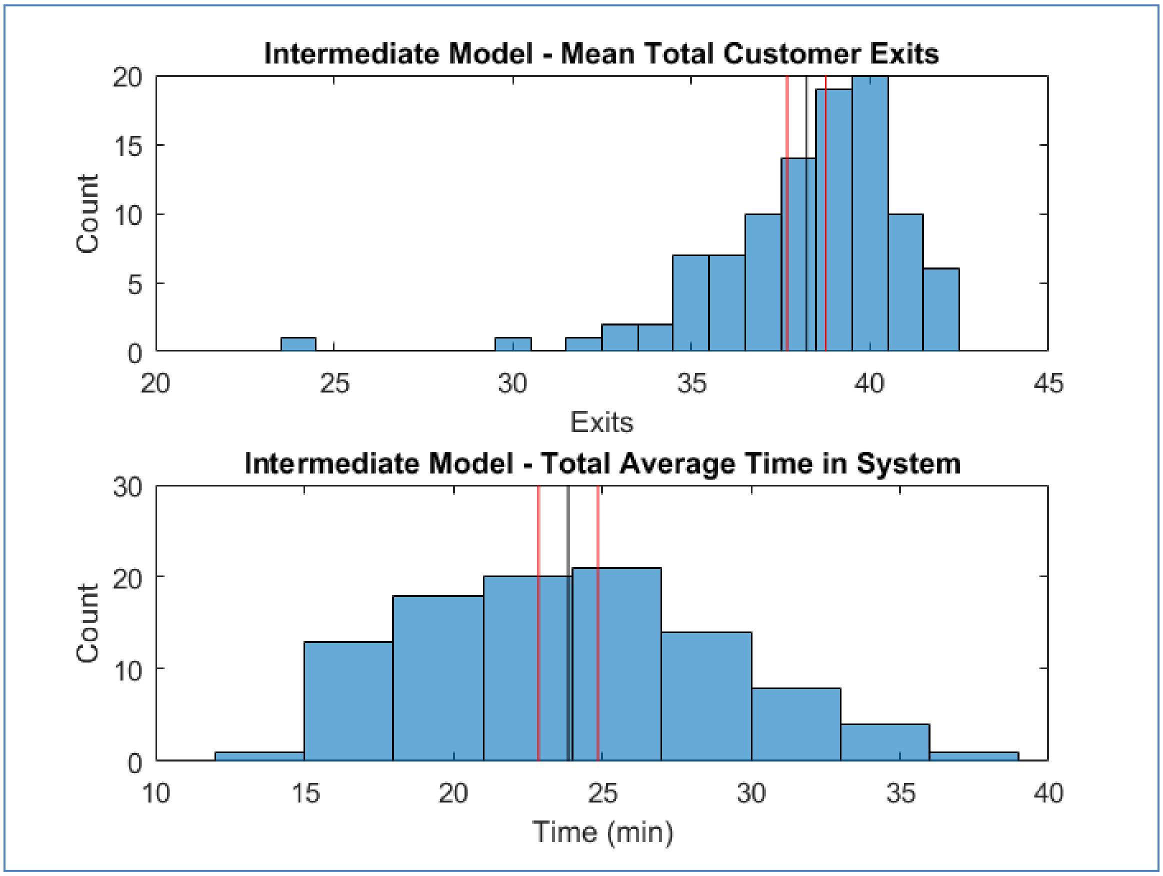


Figure 6 Intermediate Model Histograms for Customer Exits and Total Time in System

The mean total customer exist is slightly left skewed, which should acceptable for any inferences related to this analysis. The distribution of mean time in the system for customers is fairly symmetric and is adequate for analysis.

The following is the result of a two sample t-test conducted using Minitab.

Two-Sample T-Test and CI: base, intermediate

```
Two-sample T for base vs intermediate

                 N   Mean  StDev  SE Mean
base           100  28.62   3.41     0.34
intermediate   100  38.22   2.77     0.28


Difference = mu (base) - mu (intermediate)
Estimate for difference:  -9.60000
```

```
95% CI for difference:  (-10.46705, -8.73295)
T-Test of difference = 0 (vs not =): T-Value = -21.84  P-Value =
0.000  DF = 189
```

The test was conducted at the 5% significance level and assumed unequal variances. The low p-value indicates that the test is significant at the 5% level, and supports our assertion that the intermediate model is a statistical and practical improvement over the base model. The restaurant could justify pursuing this model if no additional analysis was desired.

The result of similar tests for all models can be found in Appendix D and will be discussed further in part 5 on advanced models.

5.3.3. Conclusion

It appears that the effect of moving one employee into the kitchen to help process orders, and away from the front counter is a very sensible change to the restaurant's operations. The improvement in mean total customers processed appears to be of statistical and practical significance.

5.4. Advanced Models

5.4.1. Introduction

The results of the intermediate model are a promising start, so we decided to further refine our analysis by consider advanced models for the restaurant.

The intermediate model was used as input for ProModel's companion software SimRunner. Figure 7, below, shows the importing of the intermediate model into SimRunner.

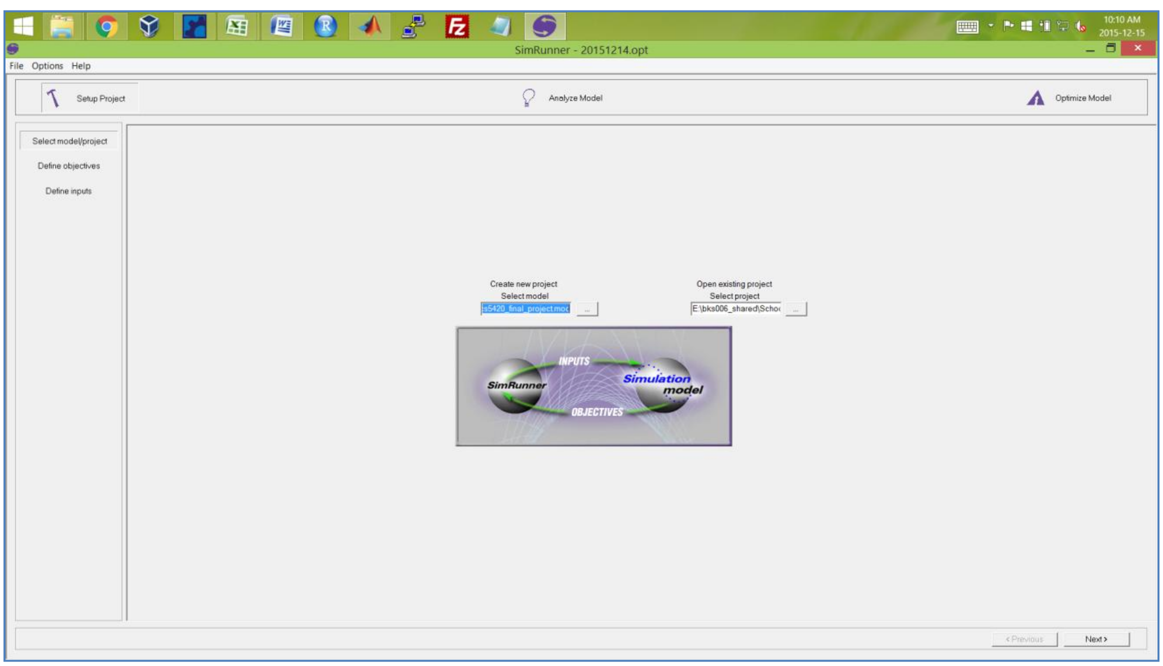
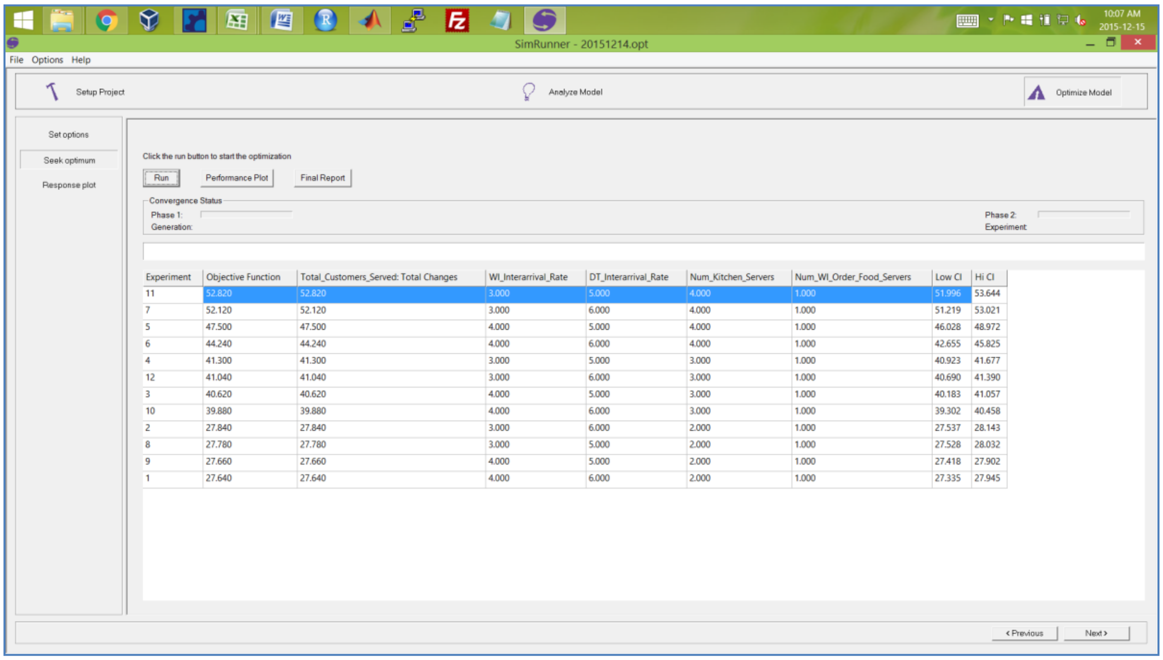


Figure 7 Importing Intermediate Model into SimRunner

The SimRunner software is designed to facilitate optimal model selection for a given simulation and model parameters. We imported our intermediate model into SimRunner and defined some parameters, such as a range of inter-arrival times, and total customer exits as our optimization function. SimRunner then identified several optimal models shown in Figure 8 below.



Experiment	Objective Function	Total_Customers_Served: Total Changes	WI_Interarrival_Rate	DT_Interarrival_Rate	Num_Kitchen_Servers	Num_WI_Order_Food_Servers	Low CI	Hi CI
11	52.820	52.820	3.000	5.000	4.000	1.000	51.996	53.644
7	52.120	52.120	3.000	6.000	4.000	1.000	51.219	53.021
5	47.500	47.500	4.000	5.000	4.000	1.000	46.028	48.972
6	44.240	44.240	4.000	6.000	4.000	1.000	42.655	45.825
4	41.300	41.300	3.000	5.000	3.000	1.000	40.923	41.677
12	41.040	41.040	3.000	6.000	3.000	1.000	40.690	41.390
3	40.620	40.620	4.000	5.000	3.000	1.000	40.183	41.057
10	39.880	39.880	4.000	6.000	3.000	1.000	39.302	40.458
2	27.840	27.840	3.000	6.000	2.000	1.000	27.537	28.143
8	27.780	27.780	3.000	5.000	2.000	1.000	27.528	28.032
9	27.660	27.660	4.000	5.000	2.000	1.000	27.418	27.902
1	27.640	27.640	4.000	6.000	2.000	1.000	27.335	27.945

Figure 8 Optimal Models Generated by SimRunner

We then selected four candidate advanced models from Figure 8 above simulate in ProModel. The result of running these models is the focus of this analysis.

5.4.2. Analysis

The results of running the candidate models suggested from SimRunner in ProModel are displayed in Table 5 as below.

SimRunner ranks the models in descending order by the objective function, which we defined as a ProModel variable in the original simulation. We have highlighted the models we choose to examine, including the fifth model and excluding the fourth, because the results are very similar, but the parameters are different, which allows for a broader scope of analysis.

We wanted to be able to analyze and propose models for different levels of walk-in and drive-through inter-arrival rates for varying levels of servers in the kitchen. As was uncovered in the base model analysis, the number of kitchen servers is the primary bottleneck to processing customers.

Table 5 SimRunner Optimized Models

Model	Obj Function	WI Total Exits	DT Total Exits	WI	DT	Cooks	Low CI 95%	Hi CI 95%
Adv1	50.50	30.65	19.85	3	5	4	49.60	51.40
Adv2	48.82	31.90	16.92	3	6	4	47.75	49.88
Adv3	46.30	25.18	21.12	4	5	4	45.09	47.52
	42.02	26.18	15.83	3	5	3	40.95	43.08
Adv4	41.88	24.28	17.60	4	6	4	40.30	43.47
	40.63	26.48	14.15	3	6	3	39.64	41.63
	39.33	20.98	18.35	4	5	3	38.72	39.95
	38.42	22.20	16.22	4	6	3	37.55	39.29
	38.03	24.73	13.30	3	5	2	36.24	39.83
	35.95	25.33	10.62	3	6	2	34.33	37.57
	30.17	16.17	14.00	4	5	2	29.08	31.26
	28.45	16.32	12.13	4	6	2	27.56	29.35

We have labeled the models as Adv1, Adv2, Adv3, and Adv4.

We know from the intermediate model that the restaurant can employ three kitchen servers by moving one front counter employee back into the kitchen. We are interested in analyzing the results of using four kitchen servers under all inter-arrival rates to see if this provides additional flexibility to unpredictable and perhaps fast changing customer inter-arrival rates. The results of Table 5 can also be found in Appendix A.

We see that the number of kitchen servers is an influential variable, as all the top models have the maximum number of servers in the kitchen, which in this analysis are four servers.

The next most influential variable appears to be the walk-in inter-arrival rate, labeled as WI in Table 3, as the top two models has walk-in inter-arrival rates of three minutes apart.

Table 6 below shows a summarized cross-section of information for all models.

Table 6 Selected Output Values for All Models

Individual Model Output Values						
Item	Models					
	Base	Inter	Adv1	Adv2	Adv3	Adv4
Mean total customers processed	28.62	38.22	49.97	49.18	45.16	43.56
Mean total time in system	33.18	23.86	21.81	20.20	17.61	17.20
Mean customer balks	2.43	0.19	0.45	0.15	0.04	0.00
Mean table utilization rate	3.69	5.52	7.50	8.08	5.96	6.30

Values in Table 6, as well as the values in Table 4 and Table 2 will differ slightly from those in Table 5, because once optimal models were obtained from SimRunner, these parameter values were then used to simulate 100 replications of the four optimal models in ProModel.

As mentioned in the analysis of the intermediate model, and shown in Appendix D, each of the advanced model's mean total customer exists are statistically significant at the 5% level when compared to the intermediate model. So, each advanced model should be preferred to the intermediate and base models, all things remaining equal.

For the user's convenience, plots of each of the advanced models, similar to Figure 6 above, are found in Appendix F. Figure 7 shows a comparison of occupancy percentages for the kitchen server in the Base Model and Adv1 Model.

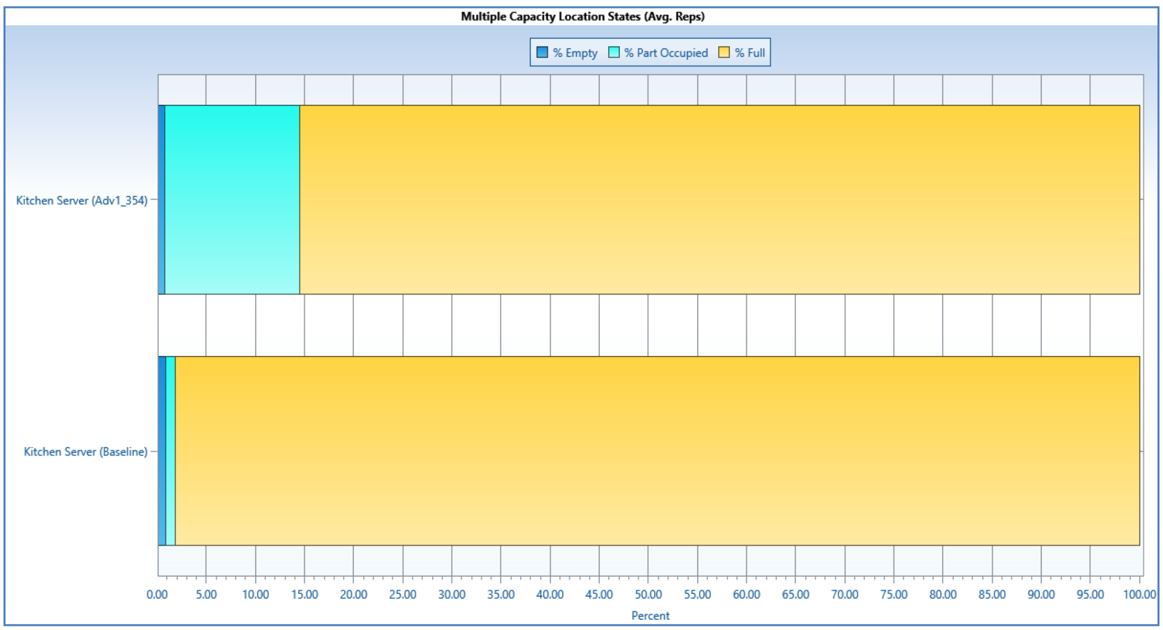


Figure 9 Comparison of Kitchen Server Occupancy Percentages

The Adv1 Model has reduced the percentage full from 98% down to roughly 85%. This is still too high, as the kitchen server utilization rate is still above 90%.

5.4.3. Conclusion

The model labeled Adv1 appears to be the most desirable of the four optimal models suggested by SimRunner. This model would require only the addition of a single kitchen server and it would increase the mean total customers served by 75% over the base model, while reducing average customer time in the system by roughly 34%. The model would also provide a little more protection to handle an unexpected rush of customer arrivals.

5.5. Analysis Limitation and Strengths

This project took the approach of emphasizing a more quantitative and statistical view point of discrete simulation analysis. We feel that this has many benefits, such as making use of the deep insight afforded by statistical tools and methods.

We feel that this approach may facilitate the client's acceptance of the results, as all recommendations should be supported by sound statistical analysis. Most importantly, sound statistical analysis is defensible, supported by data that the client should be able to review and examine on their own if needed or desired.

A limitation of this approach is that the analyst must develop some background in statistical methods and analysis, if they do not already possess these skills.

6. Proposal for Future Work

An effort should be made to investigate ways to provide the kitchen with additional servers. Given that the table utilization seems to be low, perhaps tables could be removed to make room for additional kitchen equipment.

Figure 10 shows individual histograms for walk-in and drive-through values for each of the advanced models. A future project should try to expand upon the analysis done in this report and dig more deeply into the differences in these distribution values. Some of the titles in Figure 10 are a bit difficult to see, so each plot has been reproduced in Appendix G. The intent of Figure 8 is to highlight the idea that under some advanced models the walk-in and drive-through customers are quite segmented. This is an area that we feel would be worthy of additional analysis.

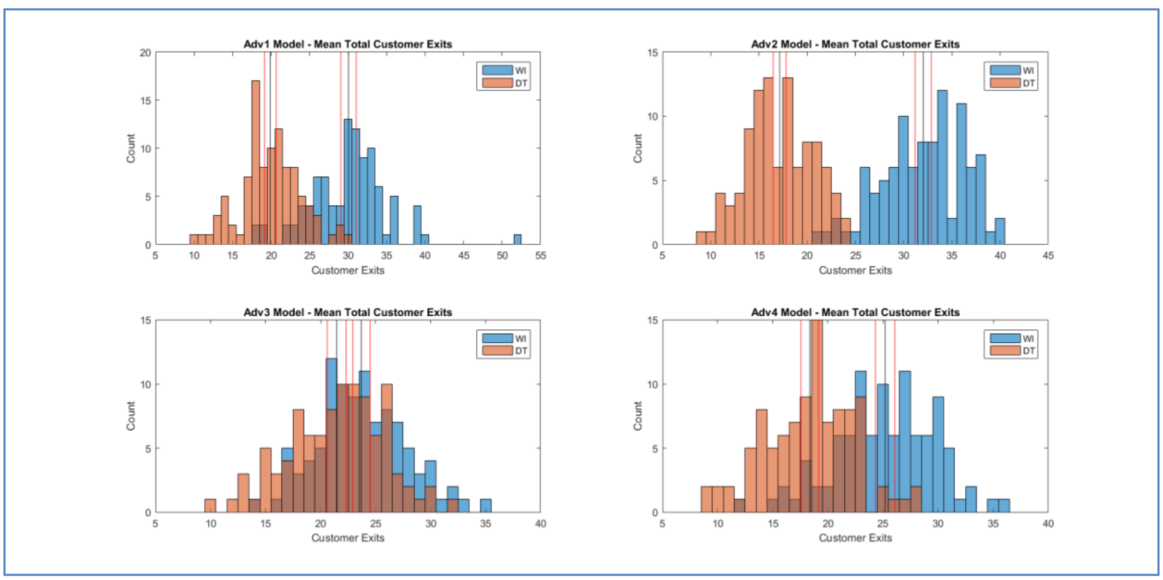


Figure 10 Walk-in and Drive-Through Distributions for all Advanced Models

We feel that a lot of the analysis that has been done in this report could be expanded to go broader and deeper.

An additional idea that we've run out of time to pursue is to more deeply examine some of the probabilistic aspects of customer exits and wait times. An examination and comparison of their cumulative distribution shape and analytic properties would be useful information for the restaurant. Such as, "What is the probability that greater than 40 customers will be served in the next 1 hour, 1.5 hours, 2 hours?" Questions such as these and other similar probabilistic questions could perhaps provide an additional metric upon which to score desirable models.

7. Conclusions

Given the information provided by Harry's Drive-Through Restaurant, we were able to establish an input-output model for analysis, and developed a base model as a bench mark upon which to compare additional models.

We examined the performance of the base model and noticed that the front counter servers were particularly underutilized, while the kitchen servers were overwhelmed with orders. This lead to the development of the intermediate model, which essentially moves one of the front counter employees into the kitchen to help process orders.

Using Minitab, we conducted a two sample hypothesis tests, or t-test, comparing the mean total customer exits of the base and intermediate models. These parameter values were found to be statistically significant at the 5% level.

We then took this intermediate model and imported it into ProModels companion software and model optimizer called SimRunner. SimRunner helped us identify four candidate advanced models, whose parameter values we took and ran simulations for these models in ProModel.

We also ran two sample hypothesis tests for each of the advanced models compared the mean total customer exits against the intermediate model. Each was found to be statistically significant at the 5% level, which suggests that each model is an improvement over the intermediate and base models.

We then briefly discussed some of the strengths and weaknesses of a more statistical and quantitative approach toward discrete simulation analysis.

We also addressed some of the short shortcomings of our analysis and considerations for future analysis, such as studying more deeply the differences in walk-in and drive-through customer activity.

8. References

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Appendix A

Table 7 SimRunner Optimized Customer Output Values

Model	Total Exits	WI Exits	DT Exits	WI	DT	Cooks	Low CI 95%	Hi CI 95%
Adv1	50.50	30.65	19.85	3	5	4	49.60	51.40
Adv2	48.82	31.90	16.92	3	6	4	47.75	49.88
Adv4	46.30	25.18	21.12	4	5	4	45.09	47.52
	42.02	26.18	15.83	3	5	3	40.95	43.08
Adv4	41.88	24.28	17.60	4	6	4	40.30	43.47
	40.63	26.48	14.15	3	6	3	39.64	41.63
	39.33	20.98	18.35	4	5	3	38.72	39.95
	38.42	22.20	16.22	4	6	3	37.55	39.29
	38.03	24.73	13.30	3	5	2	36.24	39.83
	35.95	25.33	10.62	3	6	2	34.33	37.57
	30.17	16.17	14.00	4	5	2	29.08	31.26
	28.45	16.32	12.13	4	6	2	27.56	29.35

The reader should note that total values are mean values from 60 replications of each combination of walk-in inter-arrival rates, drive-through inter-arrival rates, and the number of cooks.

Appendix B

The following tables provide the same, but sorted in different orders.

Table 8 Utilization by Name and % Utilization

Name	Replication	Scenario	% Utilization
Kitchen Server	Avg	Adv4_464	81.38
Kitchen Server	Avg	Adv3_454	84.71
Kitchen Server	Avg	Adv2_364	91.90
Kitchen Server	Avg	Adv1_354	93.84
Kitchen Server	Avg	Intermediate	95.12
Kitchen Server	Avg	Baseline	98.64
Table Server	Avg	Baseline	3.69
Table Server	Avg	Intermediate	5.52
Table Server	Avg	Adv3_454	5.96
Table Server	Avg	Adv4_464	6.30
Table Server	Avg	Adv1_354	7.50
Table Server	Avg	Adv2_364	8.08
WI Order Food Server	Avg	Baseline	15.85
WI Order Food Server	Avg	Intermediate	38.71
WI Order Food Server	Avg	Adv3_454	39.97
WI Order Food Server	Avg	Adv4_464	40.95
WI Order Food Server	Avg	Adv1_354	51.53
WI Order Food Server	Avg	Adv2_364	53.86

Table 9 Utilization by Scenario and % Utilization

Scenario	Replication	Name	% Utilization
Adv1_354	Avg	Table Server	7.50
Adv1_354	Avg	WI Order Food Server	51.53
Adv1_354	Avg	Kitchen Server	93.84
Adv2_364	Avg	Table Server	8.08
Adv2_364	Avg	WI Order Food Server	53.86
Adv2_364	Avg	Kitchen Server	91.90
Adv3_454	Avg	Table Server	5.96
Adv3_454	Avg	WI Order Food Server	39.97
Adv3_454	Avg	Kitchen Server	84.71
Adv4_464	Avg	Table Server	6.30
Adv4_464	Avg	WI Order Food Server	40.95
Adv4_464	Avg	Kitchen Server	81.38
Baseline	Avg	Table Server	3.69
Baseline	Avg	WI Order Food Server	15.85
Baseline	Avg	Kitchen Server	98.64
Intermediate	Avg	Table Server	5.52
Intermediate	Avg	WI Order Food Server	38.71
Intermediate	Avg	Kitchen Server	95.12

Appendix C

Table 10 Base Model 95% CI Values for Exits and Wait Time

Base Model					
Item	Sample Size	Std Dev	Lower 95% CI	Mean	Upper 95% CI
Mean total customers processed	100	3.41	27.95	28.62	29.28
Mean total time in system	100	5.74	29.29	33.18	34.30

Table 11 Intermediate Model 95% CI Values for Exits and Wait Time

Base Model					
Item	Sample Size	Std Dev	Lower 95% CI	Mean	Upper 95% CI
Mean total customers processed	100	100	2.76	37.67	38.22
Mean total time in system	100	100	5.09	22.86	23.86

Table 12 Adv1 Model 95% CI Values for Exits and Wait Time

Base Model					
Item	Sample Size	Std Dev	Lower 95% CI	Mean	Upper 95% CI
Mean total customers processed	100	100	4.48	49.09	49.97
Mean total time in system	100	100	4.67	20.89	21.81

Table 13 Adv2 Model 95% CI Values for Exits and Wait Time

Base Model					
Item	Sample Size	Std Dev	Lower 95% CI	Mean	Upper 95% CI
Mean total customers processed	100	100	4.18	48.36	49.18
Mean total time in system	100	100	3.70	19.47	20.19

Table 14 Adv3 Model 95% CI Values for Exits and Wait Time

Base Model					
Item	Sample Size	Std Dev	Lower 95% CI	Mean	Upper 95% CI
Mean total customers processed	100	100	5.31	44.12	45.16
Mean total time in system	100	100	2.75	17.07	17.61

Table 15 Adv4 Model 95% CI Values for Exits and Wait Time

Base Model					
Item	Sample Size	Std Dev	Lower 95% CI	Mean	Upper 95% CI
Mean total customers processed	100	100	5.85	42.41	43.56
Mean total time in system	100	100	3.07	16.59	17.19

Appendix D

The following are hypothesis t-tests conducted at 5% significance level, for the mean total customer exits. The base and intermediate models are statistically significant at the 5% level, so the advanced models were tested against the intermediate model to reduce the number of comparisons.

Thus, all models are statistically significant at the 5% level.

Two-Sample T-Test and CI: base, intermediate

```
Two-sample T for base vs intermediate

                N   Mean  StDev  SE Mean
base          100  28.62   3.41     0.34
intermediate  100  38.22   2.77     0.28


Difference = mu (base) - mu (intermediate)
Estimate for difference:  -9.60000
95% CI for difference:  (-10.46705, -8.73295)
T-Test of difference = 0 (vs not =): T-Value = -21.84  P-Value = 0.000  DF =
     189
```

Two-Sample T-Test and CI: intermediate, ad1

```
Two-sample T for intermediate vs ad1

                N   Mean  StDev  SE Mean
intermediate  100  38.22   2.77     0.28
ad1           100  49.97   4.49     0.45


Difference = mu (intermediate) - mu (ad1)
Estimate for difference:  -11.7500
95% CI for difference:  (-12.7914, -10.7086)
T-Test of difference = 0 (vs not =): T-Value = -22.28  P-Value = 0.000  DF =
     164
```

Two-Sample T-Test and CI: intermediate, ad2

```
Two-sample T for intermediate vs ad2

                N   Mean  StDev  SE Mean
intermediate  100  38.22   2.77     0.28
ad2           100  49.18   4.18     0.42


Difference = mu (intermediate) - mu (ad2)
Estimate for difference:  -10.9600
95% CI for difference:  (-11.9503, -9.9697)
T-Test of difference = 0 (vs not =): T-Value = -21.85  P-Value = 0.000  DF =
     171
```

Two-Sample T-Test and CI: intermediate, ad3

```
Two-sample T for intermediate vs ad3

                N   Mean  StDev  SE Mean
intermediate  100  38.22   2.77     0.28
ad3           100  45.16   5.31     0.53


Difference = mu (intermediate) - mu (ad3)
Estimate for difference:  -6.94000
95% CI for difference:  (-8.12371, -5.75629)
T-Test of difference = 0 (vs not =): T-Value = -11.59  P-Value = 0.000  DF =
     149
```

Two-Sample T-Test and CI: intermediate, ad4

```
Two-sample T for intermediate vs ad4

                N   Mean  StDev  SE Mean
intermediate  100  38.22   2.77     0.28
ad4           100  43.56   5.85     0.59


Difference = mu (intermediate) - mu (ad4)
Estimate for difference:  -5.34000
95% CI for difference:  (-6.61963, -4.06037)
T-Test of difference = 0 (vs not =): T-Value = -8.25  P-Value = 0.000  DF = 141
```

Appendix E

Table 16 Adv1 Model Input-Output Model

Advanced Model 1	
Input Model Values	
Dine-in inter-arrival rate	Exponential (3 min)
Dine-in eating time	Normal (mean = 15 min, sd = 2 min)
Drive-through inter-arrival rate	Exponential (5 min)
Time to take customer order	Uniform (.5 min, 1.2 min)
Time to cook order	Normal (mean = 8.2 min sd = 1.2 min)
Total Cooks	4
Walk-in Service Employees	1
Output Model Values	
Mean total customers processed	49.97
Mean total time in system	21.81
Mean customer balks	0.45
Mean table utilization rate	7.50

Table 17 Adv2 Model Input-Output Model

Advanced Model 2	
Input Model Values	
Dine-in inter-arrival rate	Exponential (3 min)
Dine-in eating time	Normal (mean = 15 min, sd = 2 min)
Drive-through inter-arrival rate	Exponential (6 min)
Time to take customer order	Uniform (.5 min, 1.2 min)
Time to cook order	Normal (mean = 8.2 min sd = 1.2 min)
Total Cooks	4
Walk-in Service Employees	1
Output Model Values	
Mean total customers processed	49.18
Mean total time in system	20.20
Mean customer balks	0.15
Mean table utilization rate	8.08

Table 18 Adv3 Model Input-Output Model

Advanced Model 3	
Input Model Values	
Dine-in inter-arrival rate	Exponential (4 min)
Dine-in eating time	Normal (mean = 15 min, sd = 2 min)
Drive-through inter-arrival rate	Exponential (5 min)
Time to take customer order	Uniform (.5 min, 1.2 min)
Time to cook order	Normal (mean = 8.2 min sd = 1.2 min)
Total Cooks	4
Walk-in Service Employees	1
Output Model Values	
Mean total customers processed	45.16
Mean total time in system	17.61
Mean customer balks	0.04
Mean table utilization rate	5.96

Table 19 Adv4 Model Input-Output Model

Advanced Model 4	
Input Model Values	
Dine-in inter-arrival rate	Exponential (4 min)
Dine-in eating time	Normal (mean = 15 min, sd = 2 min)
Drive-through inter-arrival rate	Exponential (6 min)
Time to take customer order	Uniform (.5 min, 1.2 min)
Time to cook order	Normal (mean = 8.2 min sd = 1.2 min)
Total Cooks	4
Walk-in Service Employees	1
Output Model Values	
Mean total customers processed	43.56
Mean total time in system	17.20
Mean customer balks	0.00
Mean table utilization rate	6.30

Appendix F

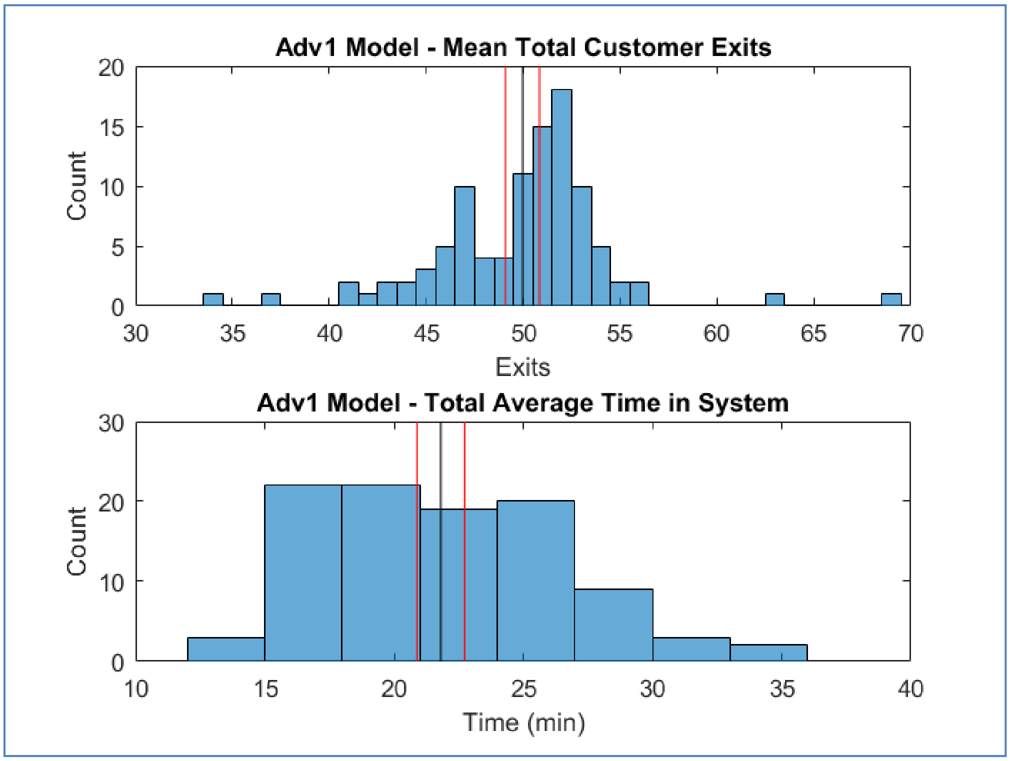

Figure 11 Adv1 Model Customer Exits and Waiting Time

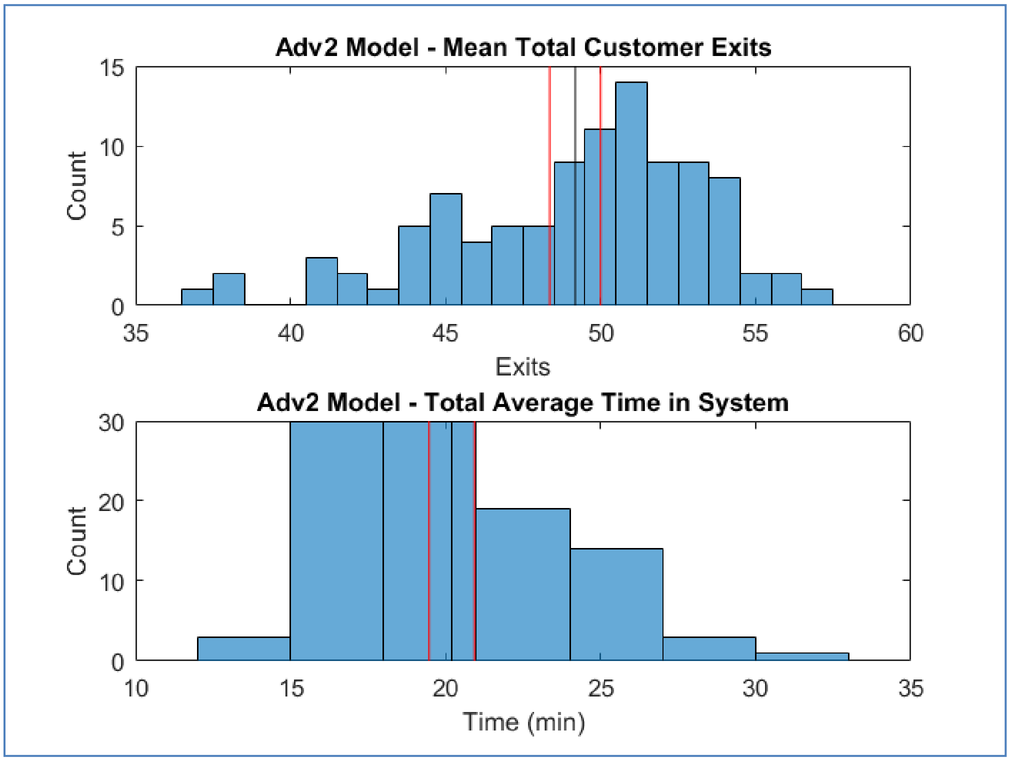

Figure 12 Adv2 Model Customer Exits and Waiting Time

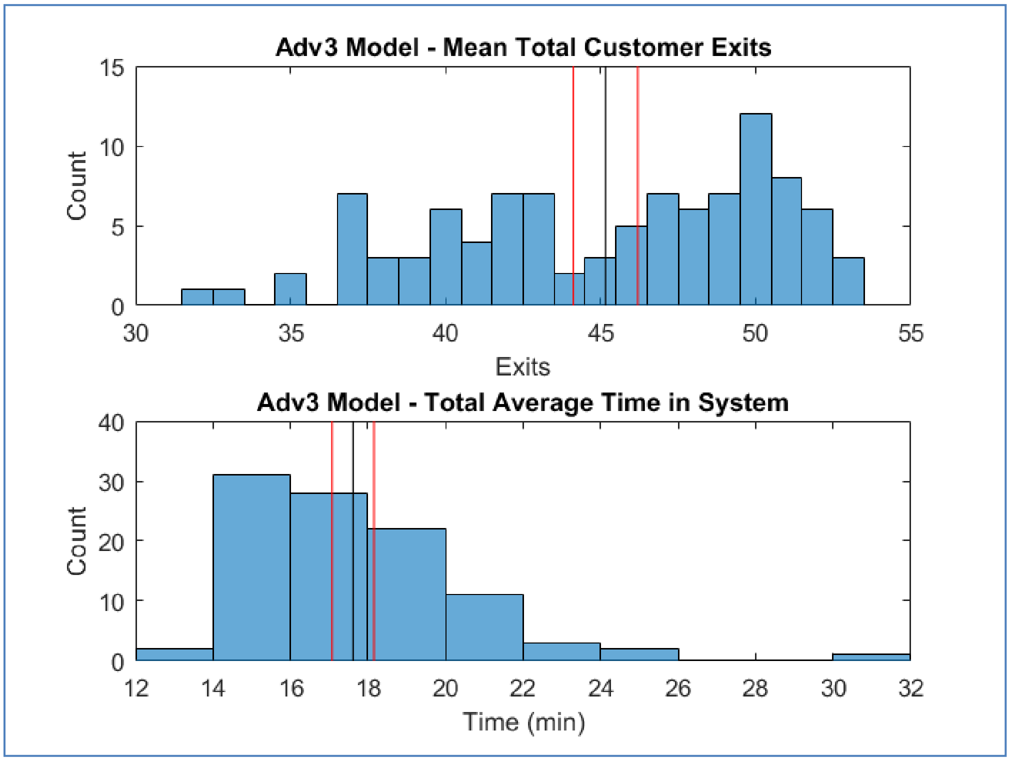

Figure 13 Adv3 Model Customer Exits and Waiting Time

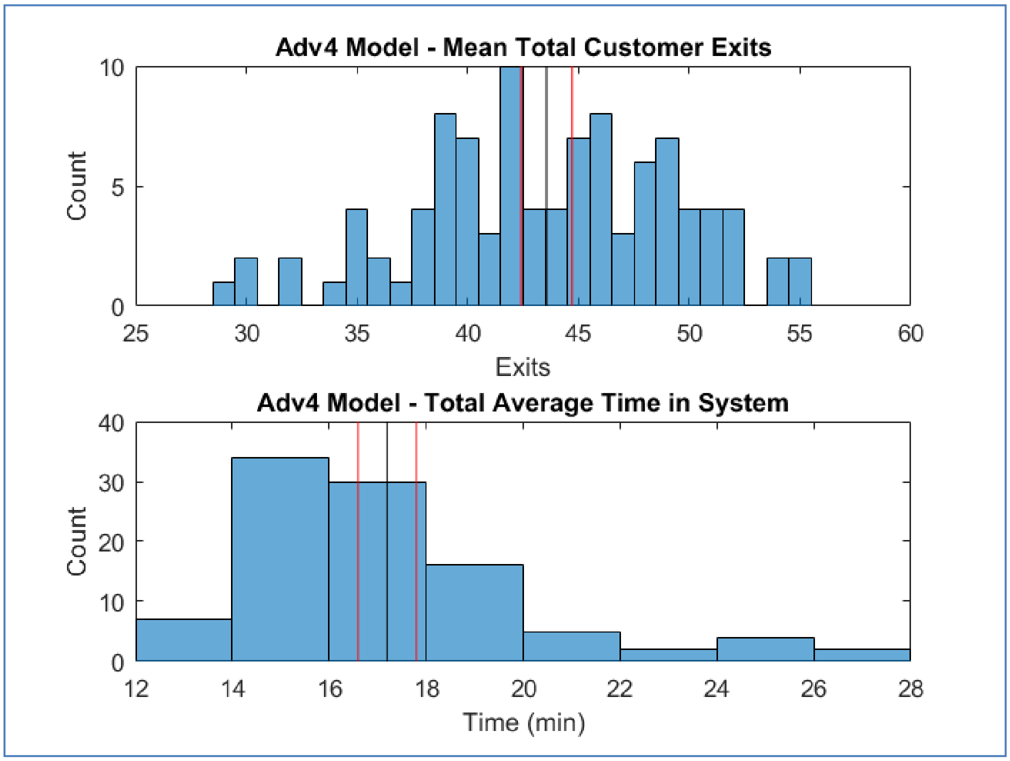

Figure 14 Adv4 Model Customer Exits and Waiting Time

Appendix G

Figures 15-19 displays a segmented mean total customer exits by customer type for each of the advanced restaurant models.

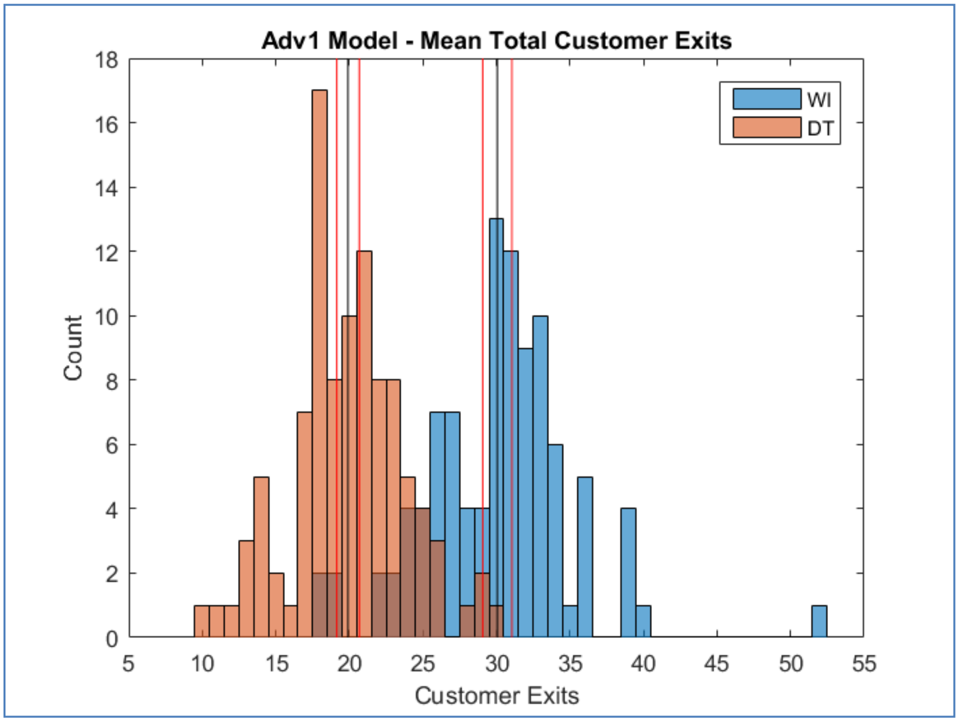

Figure 15 Adv1 Mean Total Customer Exits for WI and DT Customers

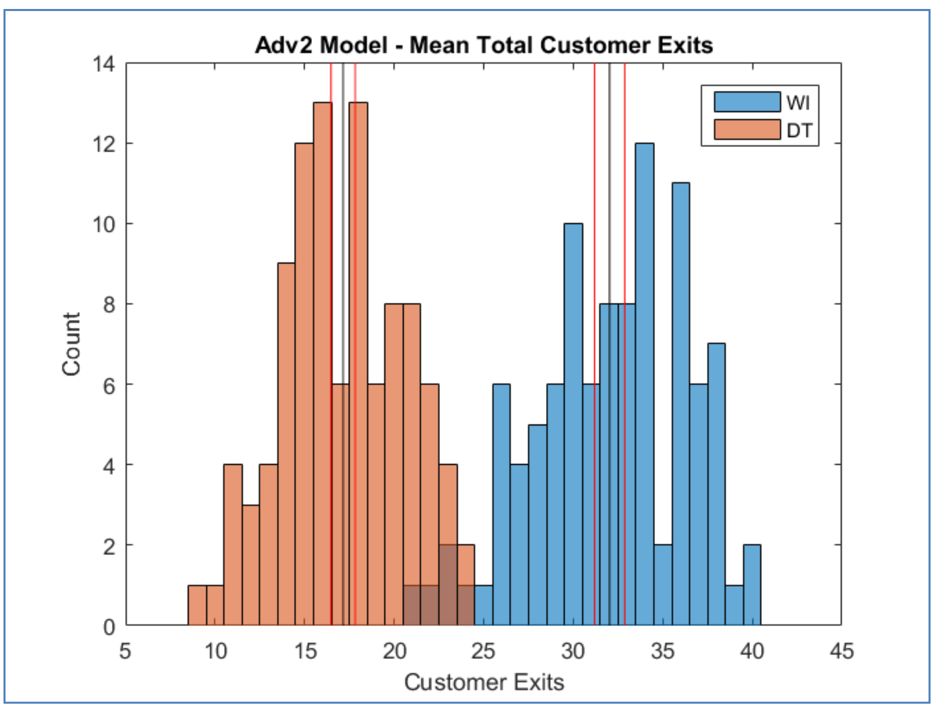

Figure 16 Adv2 Mean Total Customer Exits for WI and DT Customers

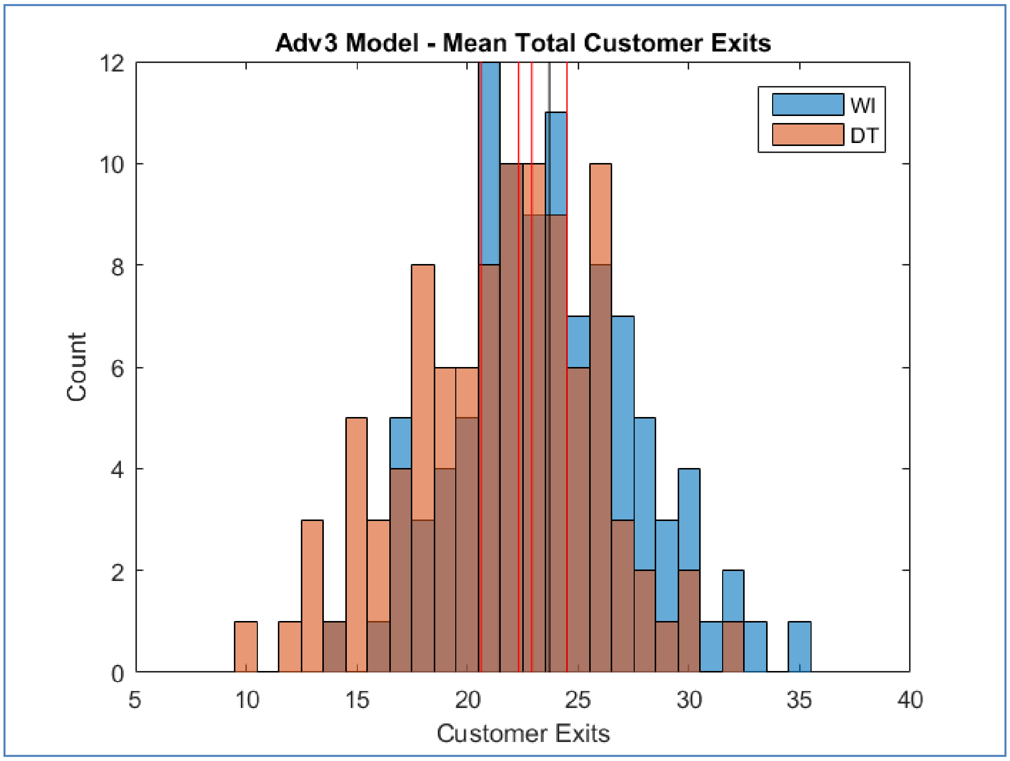

Figure 17 Adv3 Mean Total Customer Exits for WI and DT Customers

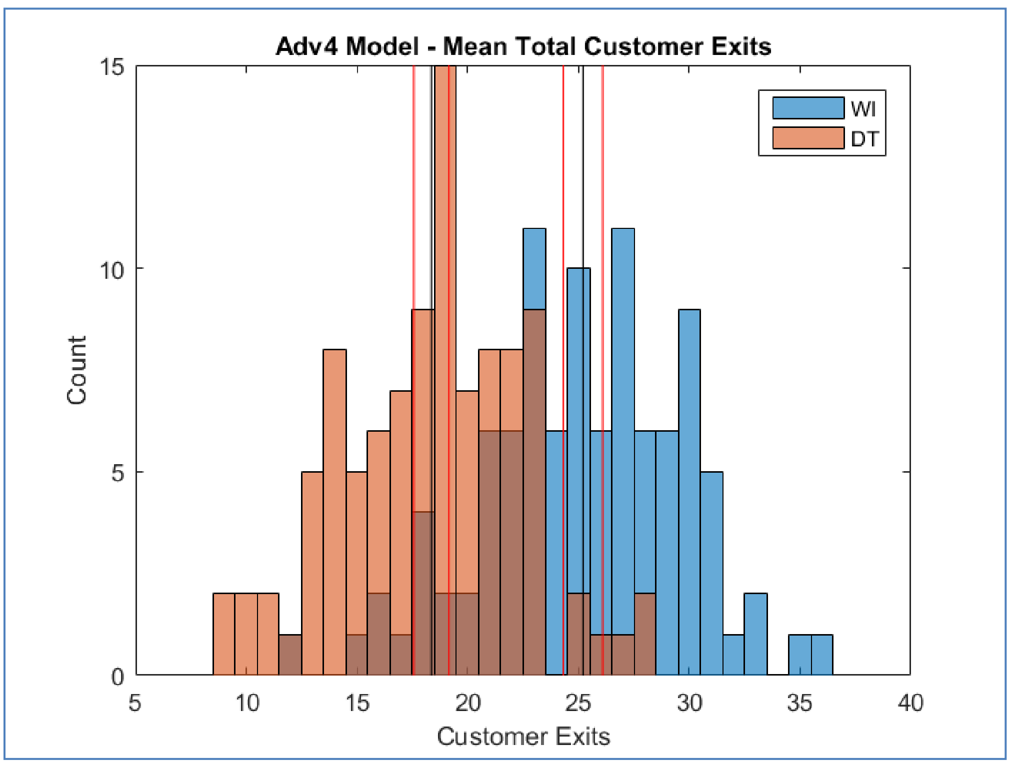

Figure 18 Adv4 Mean Total Customer Exits for WI and DT Customers