A Simulation Study to Improve Customer Waiting Time in Concessions at Jordan-Hare Stadium

by

Mengdie Chen

A thesis submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Master of Science

Auburn, Alabama
December 14, 2019

Keywords: Waiting Time, Simulation, Queue Structure,
Stadium, Concessions, Self-service

Approved by

Gregory A. Harris, Chair, Associate Professor of Industrial and Systems Engineering
Daniel F. Silva, Co-chair, Assistant Professor of Industrial and Systems Engineering
Jerry Davis, Professor of Industrial and Systems Engineering

Abstract

Attendance of college football, as well as other live events, has been dwindling for years. To enhance the fan experience, many stadiums have been investing on renovations such as installing larger screens, and building bigger luxury suites to provide premium atmosphere. However, the importance of the food & beverage experience is underestimated. The SEC's fan experience group has surveyed all SEC universities fans to better understand the importance and satisfaction of factors that contribute to the fan experience. Auburn University results (Auburn Athletics, 2019) show that the waiting time of food and beverage service has the largest negative gap between average importance and satisfaction score. To explore the methods of reducing customer waiting time at concession stands, actual data of customer arrival rate, service time and waiting time is collected from video recordings of 2 concession stands at 2 events, and is used to develop a simulation model that emulates the real situation. Then, scenario analyses are conducted to help concessions managers understand and predict how different staffing configurations, number of registers and queue design could impact the waiting time. The results show that a middle queue exit results in a slightly shorter average TIS than side queue exit. Staff role assignment and number of service stations will significantly affect the Time in System. If only 8 employees can be assigned as front workers, 6 Stations with shared server performed better than 4 stations with dedicated server. Also, separating the cup drink filling process from the checkout process will significantly reduce the average TIS for customers without cup drink orders, and will reduce the average TIS for customers with cup drink orders only if there are more two or more cup drink filling stations.

Acknowledgments

First, I would like to express my deepest appreciation to my advisor **Dr. Gregory Harris**, the completion of my thesis would not have been possible without his support and guidance. It was after taking his class that I was inspired to turn a project that I have been working on, the concessions customer experience improvement project, into a research topic. I was fortunate to have him as my advisor and got his support on conducting this research. He always steers me in the right direction when I feel lost and keeps the door open whenever I have questions or need helps. I would also like to extend my gratitude to my co-chair, **Dr. Daniel Silva**. His valuable suggestions and insights have contributed greatly to the improvement of the thesis. His intelligent, attention to detail, critical thinking and creative mind showed me how a good researcher should be like. Both of them are always there to meet with me and listen to my ideas and questions patiently, to proofread in detail and make good suggestions on my papers, and to ask me good questions to help me think through my problems. Moreover, working on the thesis with a new born baby and part-time work is extremely challenging. There were many times I felt anxiety and guilty on the delay of the work, they are always there to encourage me, support me and have confidence in me. From them not only did I gain experience in performing research but also am I inspired by their strong work ethic, professionalism and sympathy. I would also like to thank my committee member **Dr. Jerry Davis** for his valuable insights and advice on improving my thesis.

I would also like to express my sincere appreciation and gratitude to **Marcy Girton**, the Chief Operation Officer at Auburn Athletics Department. Without her support I would never have the opportunity to continue working on this research after my MBA project. It was her offered me the opportunity to continue working on concessions improvement project and provided me graduate assistantship that funded me to pursue another degree in Industrial and Systems Engineering. I will never forget that day, after my MBA capstone project presentation, she came out of the conference room immediately and give me her contact. It was one of the most important moment in my life. After that I was able to work closely with concessions management team and get significant supports to conduct my research: **Lori Arthurs**, the Chief Financial Officer at Athletics department, drove me to BestBuy immediately after knowing I needed cameras; **Jeremy Robert**, the Associate Director of Operation, gave me full access credentials to all the football games in the past two years so that I can visit all the concessions and gather first-hand information; **Kevin Duvall**, the Information Technology manager at Athletics Department, connected with security office to get surveillance videos and sponsored me a hard drive to store videos and help me keep it to ensure data security; **Jon Sirico**, Marketing manager, helped me find a best spot for cameras and install them during game day. Words can’t express how grateful I am to get their unconditionally support on everything I asked.

I’d also like to acknowledge the assistance of **Samuel Powell**, **Michelle Crowe** from Aramark team at Auburn University. They helped me go through the legal process to videotape concessions operations and introduced me to concessions group leaders. Many thanks to the **Non-Profit Organization groups** that permit me to video record their operation process and signed consent forms, without their support I would not be able to get accurate data for my research.

Last but not the least, I am deeply indebted to my family. I am so blessed to have such a perfect family. I can’t ask for better parents, parents in laws, husband and baby. My parents

Xuyang Chen, Jianmei Jiao and my parents in laws **Zhen Huang, Ping Huang** have been unconditionally supporting me all the time and given up many things for me to study at a foreign country. I can't express how grateful I am to have **Rong Huangfu** as my husband, the journey of studying abroad and having a baby is an adventure, but he is my superman, with him everything goes smoothly and I have faith that we can conquer any difficulties and challenges in our life. Finally, I would like to thank my little boy **Edison Huangfu**, thank you for giving me an incredible comfortable pregnancy period and staying healthy all the time so that I can stay focus on my research. I've been enjoying having you accompany with me for all the happy and tough moments during this research. The intention of this research is to make fans happier, I hope we will have a lot of fun together in our life and continue to do something to make other's life better.

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List of Abbreviations

SEC	South Eastern Conference
ISE	Industrial and Systems Engineering
MBA	Master of Business Administration
POS	Point of Sales
TIS	Time in System
ST	Service Time
FIFO	First-in First-out
A-D test	Anderson-Darling test
AR/VR	Augmented reality/Virtual reality

Chapter 1 Introduction

Attendance at college football games, as well as other professional sports and live events, has dwindled for years (Dellenger, 2017). Today's stadiums are facing competition from improved home-viewing options, powered by better camera angles, the growth of Augmented reality/Virtual reality (AR/VR), and multiplatform, multimedia experiences (Oracle, 2018). To create a better live atmosphere and enhanced fan experience, Auburn Athletics department has been investing in larger screens, and building bigger luxury suites. However, the importance of food and beverage services to the fan experience has been underestimated. Oracle Food and Beverage (Oracle, 2018) conducted a study "The Fan Experience: Changing the Game with Food and Beverage" that surveyed sports fans worldwide to explore the key factors of the fan experience. It reveals the importance that food and beverage contributes to the fan experience by the evidence that after safety and environment, on average, both US and International fans ranked food and beverage as their most important element of the fan experience, ahead of entertainment, technology, and amenities. Moreover, minimal waiting time is vital for the food and beverage service satisfaction. This study (Oracle, 2018) also shows that 42% of US fans said that a long waiting line has kept them from buying food or beverages at least once in the past 12 months. In addition, they also found that fans in all countries said they would potentially spend at least 30% more if wait times were cut in half.

Football fans at Auburn University Jordan-Hare Stadium have also indicated the need for concessions customer waiting time improvement. Based on an analysis of survey performed by the South Eastern Conference (SEC) about the Auburn football fan experience in the 2018 football season (Auburn Athletics, 2019), customers prioritized the length of waiting time as the fourth most important of 54 items surveyed, and the negative gap in average importance score (2.5) and average satisfaction score (3.1), at a scale of 1 (very unsatisfied) to 5 (very satisfied), is the largest among all the items surveyed. This indicates that waiting is an urgent issue that has a significant impact on the fan experience and needs to be improved.

The Auburn University Athletics Department has been applying resources to reduce the concessions waiting time. Auburn Athletics collaborated with an undergraduate student group from the Industrial and Systems Engineering (ISE) Department in the Samuel Ginn College of Engineering to conduct research on decreasing customer waiting time at concessions in 2016

(Teel, et al., 2016) and worked with a graduate student group from Auburn University Master of Business Administration (MBA) program from Raymond J. Harbert College of Business on improving fan experience at concessions in 2017 (Chen, et al., 2017). The ISE student team was focusing on decreasing the processing time by examining the design of the concession stand, worker placement and roles, and payment options. The standard concession stand layout and work assignments were demonstrated to minimize the processing time. However, with the new company, Aramark, taking over the concessions management, the new concession stand layout was implemented but no standard work procedure has been enforced. The MBA team was focusing on improving concessions' customer experience by exploring strategic plans and investment. They made suggestions based on different levels of investments such as implementing a new Point of Sales (POS) system, adopting mobile ordering technology, developing self-service concession stands, using stanchions to form single lines, and enhancing concession mapping and signage. Several suggestions from the MBA team were implemented, for example, the POS system was put in service for the 2018 football season, and more stanchions were purchased to form single serpent queue layouts, two concession stands were turned into self-service concessions, one concession stand in the student section provided mobile ordering using the Grubhub app.

After the MBA concessions research team project the author, a member of that team, continued working with the Auburn Athletics concessions management group and a third party food service company, first Sodexo then Aramark, on improving the fan experience at concessions. The POS system provided an opportunity to dig into transaction data so that service efficiency and staffing utilization can be analyzed. The data, along with discussion with the concessions management group, shows that biggest challenge of the concessions operation is getting enough workers for concession stands and implementing a standardized operating process. This is an issue because the workers are all volunteers and work to raise funds for their organizations. This also means that they have limited training and experience and may not be as engaged as a regular employee. Therefore, understanding how different number of servers, service times, queue designs and staff role assignments will impact the waiting time is necessary for designing the optimal staffing allocation and task design.

In addition, though the single queue is formed at every concession stand, the layout of the queue will impact the waiting time. The concessions stands are wide and typically have 4 to 6 cashiers in service. If the queue exit is at the extreme end at one side of the stand, there is a noticeable delay in customer awareness of the availability of a cashier at the far end of the concession stand, and then walking to that station for service. But if the queue exit is located at the middle of the concession stand, it is easier for the customer to notice the availability of cashiers across the concession stand. So, it would be interesting to research how different queue exits impact the customer waiting time. Also, based on data analytics from the POS system, more than 60% of orders include a cup drink, and as observed from the video, the cup drink is the item that takes longest time to prepare. This study will explore whether separating the drink filling process can be an effective way to reduce the overall customer waiting time.

According to Queuing Theory (Kendall, 1953), waiting time is dependent on service time, the number of servers, customer arrival rate, and the queuing discipline employed. To assist decision makers with implementing strategies to reduce the customer waiting time, this research investigates how different staff role configurations, number of service stations and queue arrangement affect waiting time, and whether the addition of self-service soda machines would reduce Average Time in System.

In this research, actual operational data was collected through video capture of the concession operations. Collected data included customer arrival rates, service times, order details and waiting time. A simulation model was developed using Simio (a popular discrete-event simulation software) and verified using actual data collected through observations of customer arrivals in the videos. Then, by adjusting the parameters (such as number of servers, service time) and model design (different queue designs and service configurations), the impact on waiting time was analyzed.

While there is a plethora of research focused on waiting time improvement in service industries such as retail, restaurants, and healthcare (Ahsan, Islam, & Alam, 2014; Hwang & Lambert, 2006; Rossetti & Pham, 2016), there is very little research conducted in the area of game day concessions services. The main contributions of this research are as follows.

First, this study provides a quantitative reference for improving concessions operation efficiency, reducing customer waiting time and enhancing the fan experience in the sports or event management industries.

Second, this study used actual customer arrival rates and service time data to identify customer arrival patterns and opportunities for improvement. In addition, a simulation model was developed, which provides flexibility for adjusting multiple variables, thus, the impact of factors on waiting time can be evaluated.

Finally, by leveraging a quantitative study and model development, this research led to the development of a decision making tool that can assist concession managers in making business decisions through sensitivity analysis and setting their own thresholds of acceptable waiting time. It will also help develop and implement standard operating processes while taking into consideration environment limitations.

The remainder of this document is organized as follows. Chapter 2 reviews previous research on customer waiting time and customer satisfaction, and simulation models applied to the Quick Service industry and waiting time management. Chapter 3 specifies the research method including data collection, model development, and experiment design. Chapter 4 further discusses the experiment design and result analysis. Finally, Chapter 5 summarizes the take-away and makes actionable recommendations to reduce the customer waiting time.

Chapter 2 Literature review

The importance of food and beverage service on the fan experience in the Sports and Entertainment industry has been documented through a world-wide customer survey conducted by Oracle (Oracle, 2018). The survey provides evidence that fans worldwide view food and beverage as an important element of their game day experience, and rank it head of entertainment, technology, and amenities. Analysis of the data shows that the main issue for food and service is the waiting time. The Oracle study also shows that 42% of fans in the US said that a long waiting line has kept them from buying food or beverages at least once in the past 12 months. Furthermore, the negative impact of waiting at concessions on the game day experience has been identified through an SEC post season fan experience survey (South Eastern Conference, 2016), which was designed by SEC fan experience group and distributed to season ticket holders at fourteen SEC universities after the conclusion of the football season. The Auburn University survey results of 2018 football season (Auburn Athletics, 2019) show that fans in the general seating area prioritize the length of waiting time as the fourth most important of 53 items surveyed. On a scale of 1 (very unsatisfied) to 5 (very satisfied) the negative gap (-0.6) in average importance score (2.5) and average satisfaction score (3.1), is the largest among all the items surveyed. Ole Miss University Athletics also has similar results that their fans rank concessions length of wait time (3.06) as ninth most important out of 53 elements surveyed, while also accounting for the largest negative gap (-0.43) of all elements measured for the general seating audience (OleMiss Football Survey Results 2018, 2019).

Currently, to the best of our knowledge, there is no published research about concessions waiting time improvement in stadiums. However, the research on waiting time and customer satisfaction, queuing management, and simulation studies on waiting time reduction can be used to provide insight for this study.

2.1 Relationship between waiting time and customer satisfaction

Waiting for service is a common phenomenon in life. Research has demonstrated solid evidence that a long waiting time has a negative impact on customer satisfaction in the service industry (Taylor, 1994; Tom & Lucey, 1997; Pruyn & Smidts, 1998). Maister (1984) first illustrated the waiting time problem from a psychological perspective. His research indicates that satisfaction is determined by the gap of perception and expectation and listed 8 factors that lead to negative waits. Later a series of empirical studies show the relationships between the perceived waiting time and actual waiting time. Hornik (1984) investigated the relationship between perceived and actual wait time in supermarket and found that there is a 2.65 minutes overestimation of perceived wait time compared with actual wait time on average. Lee (2004 & 2006) surveyed customers from a cafeteria about the relationship between perceived waiting time, expected waiting time and satisfaction score. The results show that customer satisfaction dropped sharply after 6 minutes of perceived waiting time, and the correlated objective waiting time was calculated as 2.9 minutes. Hueter & Swart (1998) found that, at Taco Bell, customer's perception of waiting time increases exponentially after the actual waiting time exceeds five minutes and achieving food delivery within an average of 3 minutes would be a significant improvement in balking rate.

Research has illustrated that, besides actual waiting time, factors that will impact customer satisfaction can be categorized into situational factors (suggested distraction, stage of process, uncertainty, unfairness, solo wait, manipulated environment) and individual factors (value of service, habit, motivation, mood, time pressure, self-distraction, perceived environment, self-explanation) (Durrande-Moreau, 1999). Other research identified that not just the length of the waiting time in line, but more importantly, the reasons for waiting determine the customer satisfaction or dissatisfaction. Customer were less satisfied when they attribute longer than expected waiting time to factors within the organization's control such as slow checkers or lack of personnel. (Tom & Lucey, 1995) In the scenario of fans waiting at concessions in a sport stadium, while investing on how more TV screens and a more comfortable environment can relieve their dissatisfaction, the factors that can be controlled by concessions such as the speed of service and the optimal staffing are important to improve customer satisfaction.

2.2 Queuing design, service options, and waiting time

Though there is a plethora of research on how single line and multiple line queues impact customer waiting time and satisfaction (Chou & Liu, 1999; Rafaeli, Barron, & Haber, 2002; Williams & Lammers, 2002), there is little to no research studies on whether the location of queue exit with regard to the position of the servers will impact the waiting time. Additionally, research can also be found that investigates whether the option of separating the queue for cup drinks will reduce the total waiting time. There are several studies that focus on a separate queue such as Friedman & Friedman (1997) who studied waiting line segmentation and found that dividing lines into premium and non-premium customers will reduce the waiting for both segments and increase revenue. It also indicates that segmenting waiting lines would be useful for a highly congested system, and a less congested system is not as sensitive to waiting line segmentation. However, there are several studies showing that a separated line, such as express checkout or self-service kiosk, may result in longer waits. Schimmel & Bekker (2013) concluded by studying the whether adding an express checkouts will reduce the waiting lines in a supermarket, that the express checkout counters can reduce 50% of express customers waiting time, but regular customers expected waiting time will increase more than 100%. Kokkinou & Cranage (2013) examined whether a self-service kiosk will reduce actual waiting-times in a hotel check in process. The results showed that the longer processing speed of the self-service kiosk and the failure rate of self-service kiosk resulted in longer waiting time, and recommend that service providers pay careful attention to the design and performance of the self-service technology.

2.3 Simulation application in reducing customer waiting time

While simulation modeling has been used in the manufacturing and healthcare industries for many years (Negahban & Smith (2014); Brailsford, Harper, & Pitt(2009)), it was not until 1981 that Burger King first started to apply simulation in the fast food industry. Burger King conducted operations research and utilized simulation modeling to identify the most efficient restaurant design and optimum number of employees needed to serve customers to increase sales (Swart & Donno, 1981). Taco Bell also developed simulation models to determine the specific relationship between speed of service and revenues result in a millions of dollars of savings in labor cost (Hueter & Swart, 1998). Curin, et al. (2005) modeled several service scenarios and evaluated the customer waiting time for Tim Horton's restaurant on the University of Michigan campus. The impact on waiting time by adding an additional worker and assigning this worker as a cashier, runner, or food server is evaluated and the research suggested an optimal server allocation to reduce customer system time by over two minutes per customer. Lee & Lambert (2008) developed a simulation model based on actual data from a cafeteria showing that adding additional employees can meet desired waiting times. Ahsan, et al.(2014) use a simulation model to demonstrate the reduction in waiting time by shifting a server from day shift to night for a restaurant.

Simulation has also been applied at retail businesses to improve the checkout efficiency and reduce the waiting time. Rossetti & Pham (2016) explored if a different checkout process would impact average waiting time by developing a simulation model based on data from a retail store. The results indicated a significant decrease of the average waiting time when payment is separated from the checkout area, as the payment time is much less than the checkout and bagging time. Alvarado & Pulido (2008) developed a simulation model using Promodel to research how different cashier and bagger combinations impact average time and system time with the focus on helping supermarket managers find a minimum number of cashiers and baggers needed for given level of service. Liu (2009) used a simulation model to propose a procedure of finding optimal solutions of personnel planning at a retail store using POS data.

These studies demonstrate the application of simulation in optimizing staffing and evaluating the impact of waiting time reduction. However, none of the studies researched arrival patterns, service time of concessions volunteer groups and waiting time in sports and entertainment events.

Chapter 3 Methodology

This chapter first describes the participants and data collected in this study, then follows with model development including the simulation model design, input analysis and model verification and validation.

3.1 Participants

In this study data was collected from video recordings from the Auburn University vs. University of Georgia football game in the 2017 football season and the Auburn University vs. Liberty University football game in 2018.

Data from the Auburn vs. Georgia game (at 2:30 PM, 11/11/2017) was gathered from videos previously recorded and shared with the author by the Auburn Athletics Marketing department. The concession stand located at section 41 in North End Zone, as shown in Figure 3.1, was chosen as it produced one of the highest sales totals. The use of videos for research purposes was approved by Auburn Athletics Marketing department and Auburn University Institutional Review Board (IRB), see appendix A and B.

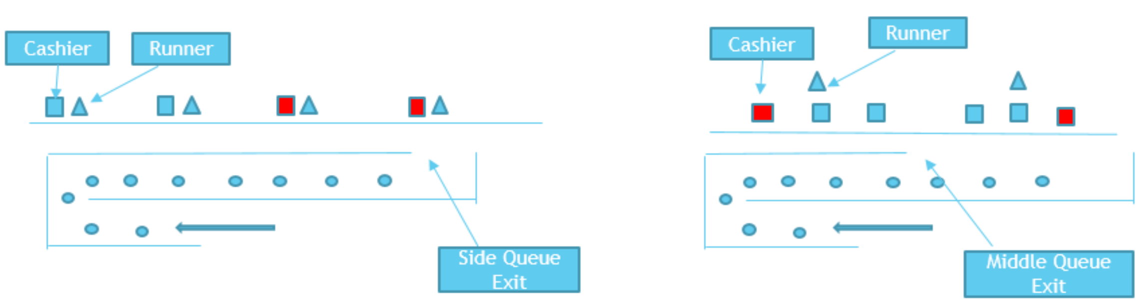
Figure 3.1 Concession stand 41

Data from the Auburn vs. Liberty game (at 3:01 PM, 11/17/2018) was gathered from videos recorded by the author, chosen because this event time and date was similar to the Georgia game in 2017. The concession stand located at section 39 in North End Zone was chosen as it generated similar sales to the Georgia game in 2017. Also the size and location of concession stands 39 and 41 are very similar. 15 workers participated in this study and their processes were video recorded with the knowledge that they were being videoed for research purposes. The consent forms, approved by IRB, were signed by all the workers inside the concession stand.

3.2 Data Collection

Two battery powered, action cameras (Go Pro) were installed above the counter on both the left and right sides of the concession stands to track the operations of each concession stand. An additional camera was attached on the wall at the concourse to record the customer queue for that concession stand. The cameras were turned on from one an hour before kickoff until they ran out of power. The battery life is approximately 3 hours.

The two concession stands use different service procedures. Section 41 has 4 service stations and two people operate one station together: One cashier takes the customer order, the other operates as a runner who fills drinks and grabs food and other bottled beverages. The layout of this concession stand is shown in Figure 3.2 (a), the square represents the cashier and triangle represents the runner. The Figure 3.2 (b) shows the service configuration of the concession stand at Section 39. It has 6 service stations, with 1 person operating a station who takes orders and retrieves items, with a runner shared for 3 stations that helps collect food and beverage for the cashiers.



(a) (b)

Figure 3.2 Concession stand configuration

Five categories of data were collected from viewing the videos: customer arrival rate, service time, order items and quantity, waiting time and travel time. The customer arrival time was tracked for section 41 on 11/11/2017 from 1:15 PM to 4:21 PM, the game start time was 2:30 PM. Arrival times for 600 customers were recorded. However, it is difficult to capture an exact arrival rate as when people arrive in a group, it is unknown if they are individual orders or they will order as group.

The service time was measured from the time that a customer arrives at the counter to the time that customer leaves the counter with their order. The service time of the two stations on the right side in Figure 3.2 (a) and two stations on opposite ends of the concession stand Figure 3.2 (b), indicated in red, were used to collect times representative of the service time for that concession stand as the placement of the cameras made it difficult to track customers at other cashier locations. 162 service time points were collected for section 41 and 141 service time points were collected for section 39.

Travel time is was measured as the time that a customer takes to move from the queue exit to the counter. The time is counted from the point when a server of a station indicates readiness, to the point when the customer arrives to that station. Because a single serpent queue is implemented at all the concession stands, the alternative of individual straight line queues for each station were not considered. A First-In, First-Out (FIFO) service discipline was assumed.

For each customer order we logged the order items and quantity of each item ordered from the video. The items sold include pretzels, pizza, nachos, bottle drink, popcorn, hotdogs, cup drink, peanuts, and candy.

To explore the question of whether or not adding a self-service drink station would reduce the waiting time, the service time without cup drink preparation was estimated based on observations from the videos. The service time spent on cup drink exclusively was determined and then excluded from the total service time. To get the new distribution of service time without the drink filling process, the service time for orders without cup drink is used.

The customer waiting time includes customer waiting in line and waiting for service, so the customer time in system is used to represent the waiting time. It is counted from the time the customer enters the queue to the time customer leaves the service counter. The actual data of customer waiting time was gathered by observations from the videos. The number of customers in line is the total number of people in line at any given time. However, it is difficult get an accurate number of people/orders in line through video observation. Each person in the line does not necessarily represent an order as many people may go to a concession stand as a group and actually represent only one order.

3.3 Model Design

To evaluate the impact that the number of cashiers, staffing role assignments, queue layouts, and separating cup drink filling process on customer waiting time, simulation modeling is the appropriate tool as it can be designed to emulate a real system and evaluate various strategies for the operation of the system (Pegden, et al., 1995). The simulation model integrates a conceptual model and programing by utilizing a computer-based statistical sampling experiments (Law, 2007). The behavior of a system, asking "what if " questions about the real system, and assisting in the design of real system can be described and analyzed by simulation (Banks, 1999).

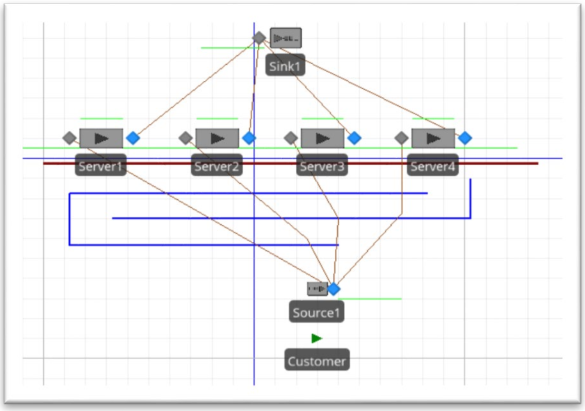
Discrete-event simulation models were developed using the Simio software platform due to ease of use and the ability to emulate actual objects and processes using object-based modeling (Smith, et al., 2018). The model was developed to consider how the number of servers, service time and queuing configuration impacted customer waiting time. The research focus is on front-end operations and does not consider the food production procedure from the back end of the concession stand operations.

Two separate, but related, models were developed to study customer waiting time, which is considered to be customer from the time the customer enters the line until they leave with their food. Thus, the Time in System (TIS) represents waiting time. The models captured the process from the point when the customer enters the queue to the time the customer leaves the counter. The serpentine queue was applied in both models with different exit points (side exit and center exit). The crossing (passing) logic of the line follows a FIFO service discipline and the customer exits the queue when there is an available server. If more than one server is open, the customer will choose the closest available server or the server that is easier to notice that they are available, which is based on observation of customer behavior in the videos. Each cashier is modeled as a separate station in the simulation. Since a customer will not go to a server unless it is available, the input buffer of each server is 0 and there's no line formed at the server. The distribution of arrival rates, and travel times were determined by the observed actual data. The processing time (service time) is determined by a distribution which is a best fit for the real data using @risk, an add-in Microsoft Excel tool that can generate data fitting distributions with a broad library of probability distributions and correlation modelling.

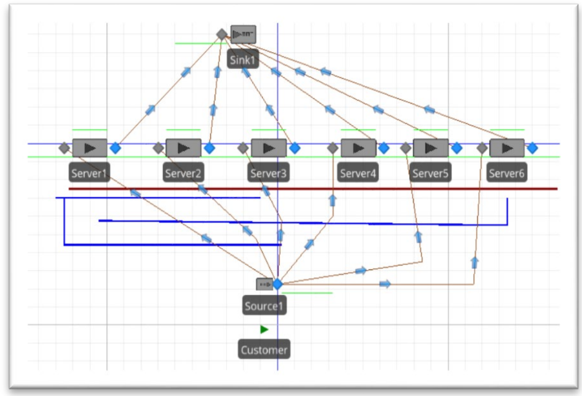
The first model (Model 1 in Figure 3.3 a) is based on the service process observed during the 2017 football season at concession stand 41.There are four server stations and each station is staffed with two workers, one serves as the cashier and the other serves as a runner. The queue exit is at the far right side of the counter and the preferred order of server choice is 4, 3, 2, 1.

The second model (Model 2 in Figure 3.3 b) is based on the service processes observed in the 2018 football season at concession stand 39. There are six service stations and each station is staffed with one cashier with one runner assigned to work with three cashiers. As we only focus on the time to serve the customer, the action of the shared runner is not directly included in this model, but only captured by the increased service time relative to having a shared runner. The queue exit is located in the middle of the counter and the preferred order of server is 4, 3, 5, 6, 2, 1 as customers are typically looking for an available station in front of them.

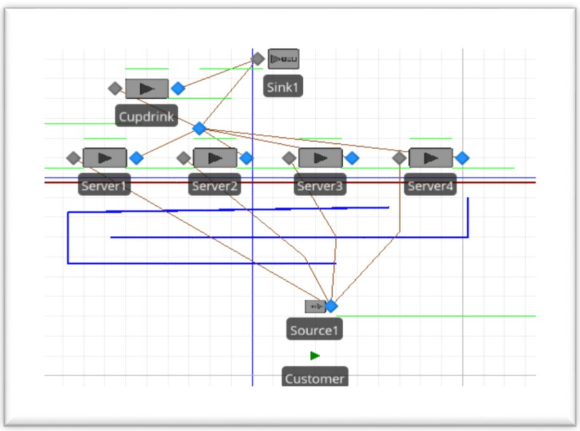
Extended Model 1 and Extended Model 2 (in Figures 3.3 c and d) removes the filling of a cup drink from the activity of the concession stand server and assumes that the customer will fill the cup drink themselves at a separate station, these are variants of Models 1 and 2 respectively. The processing time of servers are modified to exclude drink filling time based on the actual percentages observed in the videos, those customers with a cup drink in their order are assigned a new path and enter the drink self-service filling station. Those customers without cup drink orders leave the system after leaving the main service counter. The time spent on walking to the cup drink station is determined to be 10 seconds, as we assume the self-service fountain station will be installed at about 15 meters away. A discrete distribution is used to simulate the processing time of cup drink station for customers filling one cup of drink, two cups of drink and three cups of drink. The capacity of cup drink station can be adjusted under the experiment design.



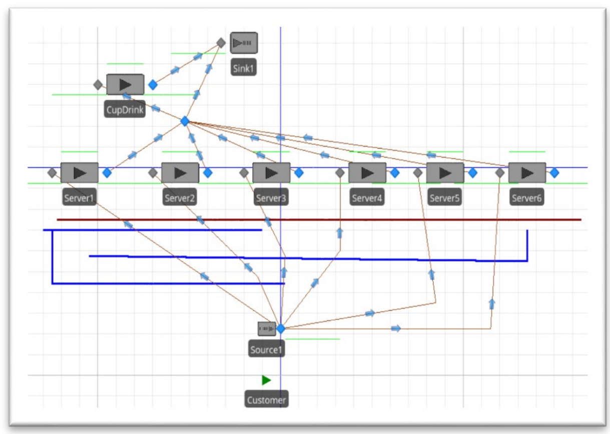
(a) Model 1



(b) Model 2



(c) Extended Model 1



(d) Extended Model 2

Figure 3.3 Simulation Model

3.4 Assumptions

Several assumptions are required made for the model to emulate the real situations based upon the limited observations and datasets.

a. All servers have the same work efficiency and the same service time distribution.

b. Customers order similar combinations of food and beverages at each station.

c. Customer arrival rate at the two concession stands are similar.

d. Customers at the concession stands have the similar purchase power and preference.

e. No server failures or breaks existed.

f. Balking and reneging do not take place

3.5 Input Analysis

3.5.1 Arrival rate

As this is a sporting event and the customers are more likely to purchase food before kickoff or around half time, the arrival rate changes over time. Thus, a nonstationary input is needed to simulate the arrival process. Therefore, the time varying arrival rate function is utilized in Simio. The arrival rate table used is shown in Figure 3.4.The number of customers arriving during 15 minute intervals was counted and used as arrival rate in this model. The peak time is in the hour before game starts and a second (smaller) peak is observed around 30 minutes after kickoff. The time segment with the fewest amount of customers arriving at the concessions stand occurs right after kick off. Arrivals during each fifteen minute interval are generated by the simulator following a Poisson process with the corresponding hourly rate. Hence inter-arrival times follow an exponential distribution and actual arrivals will differ for each replication. As noted earlier, the number of persons arriving to the queue is not necessarily the arrival rate of orders, as often multiple people go to the concession stand in a group yet represent only one order. But for this study the arrival rate is generated from the number of people arriving in a given amount of time.

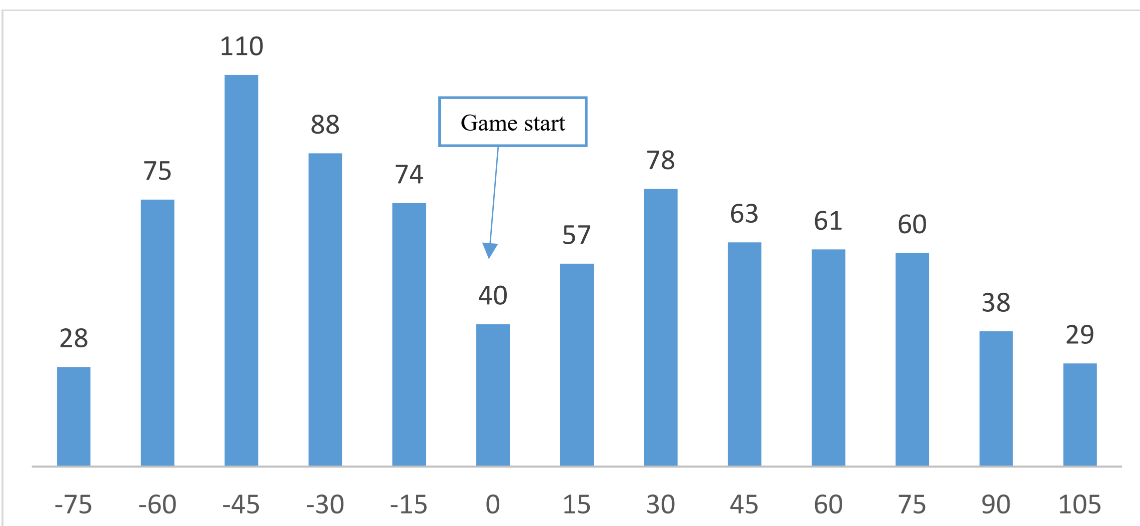


Figure 3.4 Customer arrival rate (in 15 minutes interval)

3.5.2 Service time

To find a “Good Fit” distribution that ensures the input model represents the real process, the Goodness of Fit Tests, along with graphical comparison are used. (Biller & Nelson, 2002). First, the real service time dataset was used to estimate the candidate distributions using the @risk distribution fitting function to generate fitted distributions. Then the top 3 candidate distributions ranked by the p-value goodness of fit test, Anderson-Darling (A-D) statistic, were chosen as the candidate distribution. Table 3.1 shows the results of p value from top 3 best fit distributions. The p-values of the A-D tests are larger than 0.05 for the three distributions, showing that all of the distributions are good fit distributions. Since the larger the p-value, the better fit it is, the lognormal distribution is chosen as it had highest p-value of distribution fitting for Stand 41 and second highest for Stand 39. Finally, since the best fit distribution may not be the ideal distribution (Biller & Nelson, 2002), a graphical tool can be employed that shows histogram with the candidate distributions in @risk to examine the fit, shown in Figure 3.5 and Figure 3.6, the shape of three candidate distributions are similar and fit the actual data well. A Probability-Probability Plot (p-p) plot is also used to check where the lack of fit occurs. Figure 3.7 shows an almost straight 45 degree line for all of three candidate distributions and the shapes are very similar. Considering all three candidate distributions fit the service time well, and the p-value of A-D test for lognormal distribution ranked highest for service time at Stand 41 and second at Stand 39, the lognormal distribution was used as service time distribution.

Table 3.1 Result of p-value from A-D statistic test

Concession	Pearson5	Lognormal	Loglogistic
S41	0.27	0.34	0.22
S39	0.4	0.44	0.46

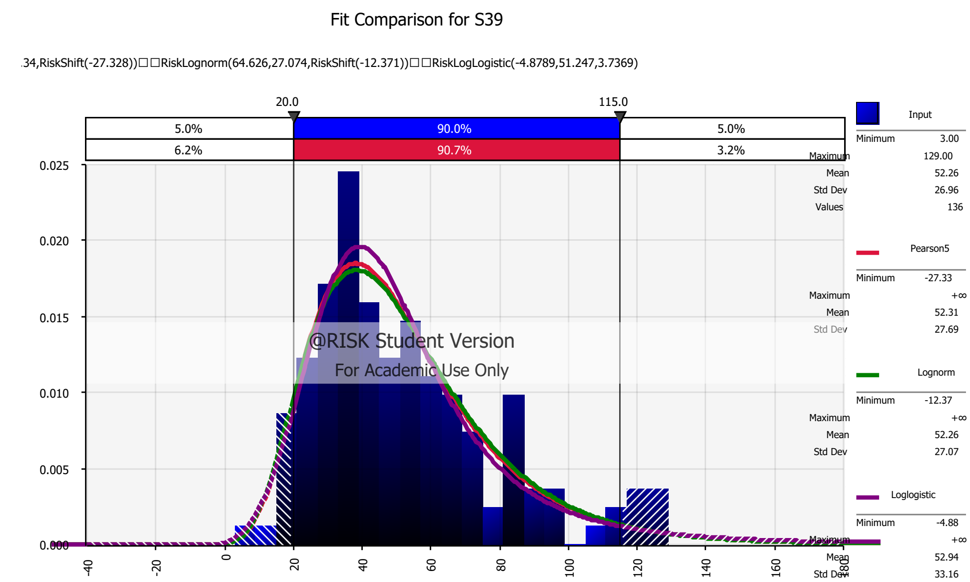


Figure 3.5 Fit Comparison for S39

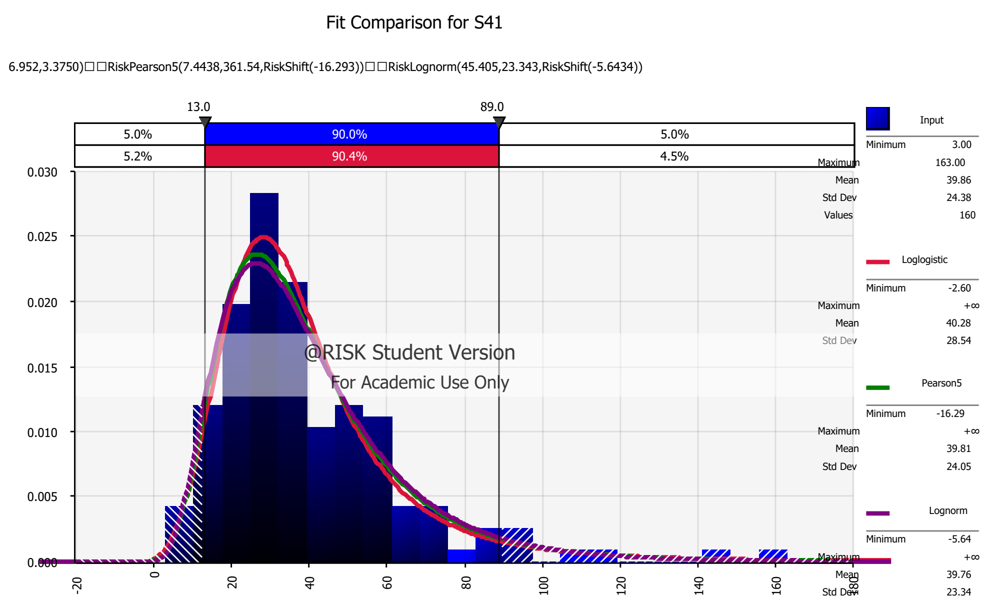
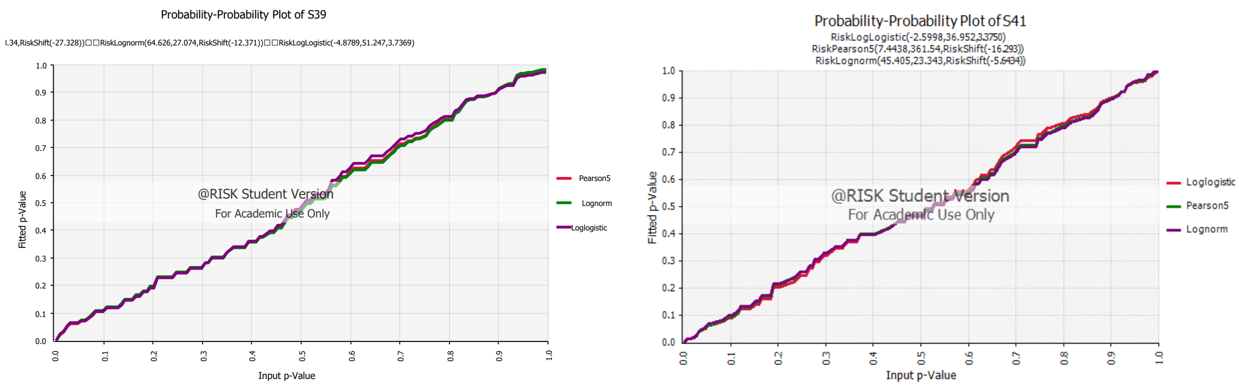


Figure 3.6 Fit Comparison for S41



(a) p-p plot of S39 (b) p-p plot of S41

Figure 3.7 Probability-Probability Plot

In Simio the Lognormal distribution uses the normalized Mean and Standard Deviation, so the parameters of Mean and Standard Deviation from the analysis are adjusted to the normalized Mean and Standard Deviation. The calculation is based on equations below.

$$\text{normalMean} = \ln(\text{LogNormalMean}^2/\text{sqrt}(\text{LogNormalMean}^2+\text{LogNormalStdDev}^2)) \text{ [EQ.1]}$$

$$\text{normalStdDev} = \text{sqrt}(\ln(1+\text{LogNormalStdDev}^2/\text{LogNormalMean}^2)) \text{ [EQ.2]}$$

The parameter of Mean and Standard Deviation comes from the @Risk distribution function and was adjusted to the parameter that is used in Simio Lognormal distribution. The result is shown in Table 3.2.For example, for service time distribution in section 39, from the @risk, the parameter of Lognormal Mean and Standard Deviation is 52.3 and 27, then it is transformed to normalized Mean and Standard Deviation, which is 3.53,0.55 in lognormal distribution in Simio. Similarity, Lognormal (39.7, 23.2) from @risk was transformed to lognormal (3.83, 0.49) in Simio, as the service time distribution in section 41.

Table 3.2 Result of Service Time Distribution

Service Time (in seconds)	**S39**	**S41**	**S39_Nocp**	**S41_nocp**
Lognormal (mean,S.D)	(52.3, 27)	(39.7, 23.2)	(39,18)	(27.3,17)
Normalized Lognormal (mean,S.D)	(3.83,0.49)	(3.53,0.55)	(3.56,0.43)	(3.14,0.57)

3.5.3 Order types

The items and quantities are tracked for each order. The menus in 2017 and 2018 are slightly different as shown in Table 3.3, no peanuts and candy were available in 2017 at concession stand 41.Concession stand 41 sells more cup drinks and fewer bottle drinks, but the popularity of other items are similar. To simplify the model, it is assumed that both concession stands sell orders of similar composition.

Table 3.3 Order Composition (% of Item Quantity)

Section/Item	**Pretzel**	**Pizza**	**Nacho**	**Bottle Drink**	**Popcorn**	**Hotdog**	**Cup drink**	**Peanuts**	**Candy**
S41 (4S)	6%	6%	3%	13%	10%	20%	43%		
S39 (6S)	2%	6%	7%	22%	14%	14%	30%	3%	1%

From the videos, it was observed that the cup drink filling process takes the longest amount of time, so the differences between orders with cup drink and orders without cup drink was investigated. To determine the service time without the drink filling process in the Extended Models (Figure 3.3 (c) (d)), the service time of orders without cup drink is used to generate the distribution for orders processing time and is shown in Table 3.2 column S39_Nocp and S41_Nocp. As can be seen the mean reduced 13 seconds at concession stand 39 and reduced about 12 seconds at concession stand 41, the stand deviation for both is also reduced. As shown in Figure 3.8, there is a statistically significant difference in service time between orders that have cup drink and orders without cup drink. The finding poses the question whether moving to a self-service process, or setting up grab&go customer service process, would reduce the waiting time.

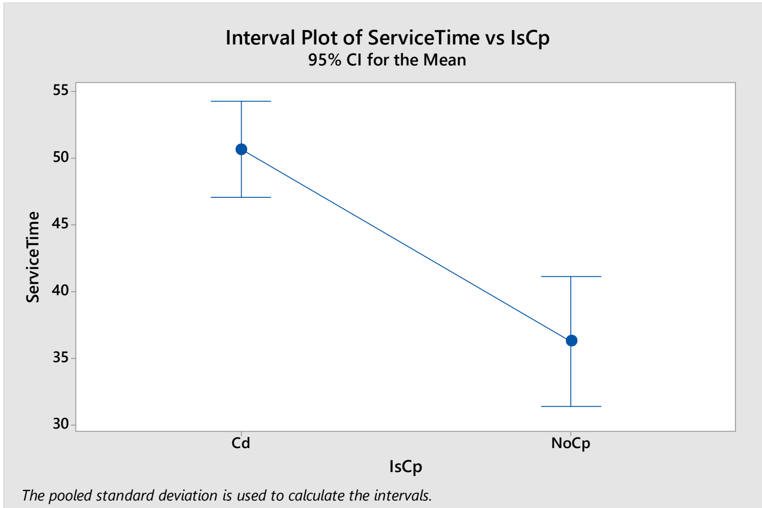


Figure 3.8 Service Time of Cup drink orders and no Cup drink orders

The cup drink order composition is also analyzed to simulate cup drink segmented process. Table 3.4 shows that 54% of orders at concession stand 41 contains cup drink and 76% of orders at concession stand 39 contains cup drink, which may be due to other factors such as the weather. In concession stand 39, 66% of cup drink orders have one cup drink, 30% of cup drink orders have two cup drink, and 4% of cup drink orders have three or more cup drink. Concessions stand 41 has a very similar cup drink orders composition. In the simulation models 3 and 4, Figure 3.2 (c) & (d), the actual cup drink orders percentage for S39 and S41 are used. The orders of S39 and S41 are combined and used for experiment design with the purpose of eliminating the impact the different order composition on TIS in Extended Model (a) and Extended Model (b).

Table 3.4 Cup Drink Order Composition

	S39	**S41**	**Combined**
# of cup drink orders	74	122	196
Total orders	136	160	296
% of cup drink orders	54%	76%	66%
one cup drink orders	49	81	130
two cup drink orders	22	38	60
3 and more cup drink orders	3	3	6
% one cup drink orders	66%	66%	66%
% two cup drink orders	30%	31%	31%
% three and more cup drink orders	4%	2%	3%

3.5.4 Travel time

Since the placement of the queue exit point impacts the travel time for customer movement to each station, the time that each customer spends moving from the end of the queue to the service station is considered. As the travel time is relatively consistent for each travel path, a fixed, deterministic travel time, equal to the average of the observed times, was used for each path. The travel time used is shown in Table 3.5.For concession stand 41, the four service station stand, the travel time in seconds is 1, 2, 4, 6 from closest to the furthest station. For concession stand 39, the six service station stand, the travel time in seconds is 5, 3, 1, 1, 3, 4 from the left to right service stations. Since we only have videos for 4 Station model with side queue exit and 6 station model with middle queue exit, the travel time for 4 station middle queue exit and 6 station side queue exit is estimated based on game day observations.

Table 3.5 Travel Time (in seconds)

Stand/Station	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6
4 Station_Side queue exit	6	4	2	1		
4 Station_Middle queue exit	3	1	1	3		
6 Station_Side queue exit	8	6	4	3	2	1
6 Station_Middle queue exit	5	3	1	1	3	4

3.6 Model Verification

3.6.1 Process verification:

To verify the simulation model, the Trace function in Simio was used to monitor each step from entity created to entity destroyed, each step is checked to see if it follows the process as designed. The service time generated from trace file was calculated to ensure this service time distribution is close to the service distribution used as input. The service time generated from Simio follows lognormal distribution with a mean of 39.8 and a standard deviation of 25.3, which is very close to the fitted service time lognormal distribution with a mean of 39.7 and a standard deviation of 23.2.The status plot of Number in System (Figure 3.9) is also used to check if the model reflects the actual situation. Figure 3.9 shows the peak time is about 20-40 minutes before game start, then followed the second peak time at around half time. Number in System dropped dramatically after game start. This reflects the actual situation as observed in the video, customers make purchases about 20-40 minutes before game starts and stop entering the line when the game starts, then customers arrive to make purchases after the first quarter.

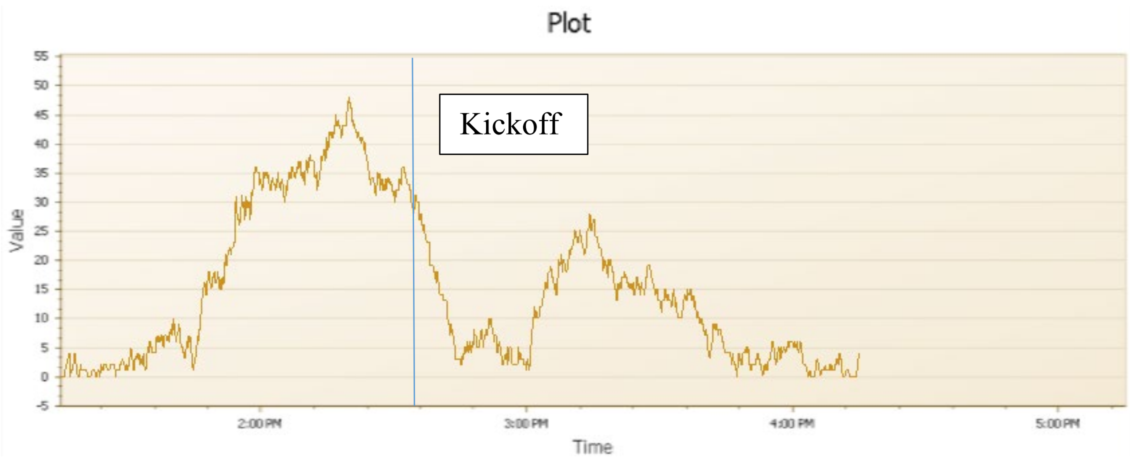


Figure 3.9 Number in System in Section 41

3.6.2 Result validation:

To compare the model output with the actual waiting time, the actual time in system for each customer must be tracked. However, due to the complication of tracking every customers waiting time in a 3-hour interval, 12 minutes of video before kickoff that includes high traffic and low traffic time was selected, 92 customers' time in system was tracked as a sample. The average waiting time was calculated to be 1.96 minutes. Then, the model was run with 100 replications to determine Average Time in System. The result, as shown in Table 3.6, shows that the average waiting time is 2.61 minutes and the half-width of a 90% confidence interval is 0.16 minutes. Although the observed average waiting time does not fall into the confidence interval of Average Time in System from the model, it is higher than the lower percentile (25%) of Average Time in System. The reason that the average waiting time in system from the model is higher than the real data is believed to that the arrival rate in the video data is counted by people, rather than by orders. Since orders could be multiple persons arriving, this results in a higher arrival rate than the actual arrival rate resulting in a longer waiting time. This will not have a negative effect on our result as the arrival rate is a fixed input variable in our model, all the models are using the same arrival rate. Thus, the higher than actual arrival rate will not have a negative impact on any comparisons, as all conclusions should hold for somewhat higher or lower arrival rates, as long as the overall trends remain the same.

Table 3.6 Simulation result of Time in System (in seconds)

Measure	Avg. TIS	90% C.I.
Mean	2.61	(2.45,2.77)
25th percentile	1.91	(1.72,2.1)
75th percentile	3.15	(2.96,3.34)

In summary, the model is verified and valid to be used to study the impact of service time, number of stations, queue design on waiting time.

Chapter 4 Experimental Methods and Results

This chapter analyzes the impact of number of stations, staff role configuration, queue layout design, and separating the cup drink filling process on customer waiting time and time in system. The first part of this chapter discusses the experiment designs with the purpose of examining the impact of certain variables. Second, this chapter presents the results from those experiments and concludes with the results of how waiting time is impacted quantitatively.

4.1 Experiment design

The scenarios based on the base models are provided in Table 4.1.Scenario 1 represents the Model 1 and scenario 2 represents Model 2.The travel time, and/or service times are adjusted in each model to compare specific scenarios to understand the impact of the parameter individually, or combined. All of the scenarios use the same arrival rate. The scenario name is used to differentiate service time, queue layout and number of service stations. For example, 4S means 4 service stations and 6S means 6 service stations, SL means side queue exit and ML mean middle queue exit, FS represents the service time of a cashier and a dedicated runner serving one station, and SS represents the service time of a cashier with a shared runner.

Table 4.1 List of scenarios with Base Model

Scenario #	Scenario Name	Change to Base Model
1	4S_SL_FS	*Model 1: Four stations, service time of one cashier and one runner to serve each station, side queue exit*
1-1	4S_ML_FS	Change Model 1 from side queue exit to middle queue exit
1-2	4S_SL_SS	Change Model 1 service time to that for one server on one station with a runner shared between stations
1-3	4S_ML_SS	Change Model 1 from side queue exit to middle queue exit and change the service time to that for one server on one station with a runner shared between stations
2	6S_ML_SS	*Model 2: Six stations, service time of one cashier serves one station with a shared runner, middle queue exit*
2-1	6S_SL_SS	Change Model 2 from middle queue exit to side queue exit
2-2	6S_ML_FS	Change Model 2 service time to that for two people (cashier + runner) serving each station
2-3	6S_SL_FS	Change Model 2 from middle queue exit to side queue exit and change service time to that for two people (cashier + runner) serving each station

The scenarios with Extended Models explored within the experiments are provided in Table 4.2.Scenario 3 represents the Extended Model 1 and scenario 4 represents Extended Model 2.These scenarios are designed to test whether having a cup drink self-service filling process separate from the casher register location affects the Time in System and how many self-service drink machines are optimal for one concession stand. All of the scenarios use the same arrival rate. The scenario name is used to differentiate service time, queue layout, number of service station, number of cup drink service stations, and cup drink order percentage used in the model. For example Cp1 represent one cup drink station and Cp2 represent two cup drink stations. MCp represent using cup drink composition of the combined orders of both stations.

The experiments that were carried out are described below:

Experiment A. Impact of queue layout

In Experiment A, how different queuing designs impact the average waiting time and maximum waiting time by changing the travel time parameter was analyzed. This can be observed though the pairwise comparisons of scenarios 1 (4S_SL_FS) and 1-1 (4S_ML_FS), scenarios 1-2 (4S_SL_SS) and 1-3 (4S_ML_SS), scenarios 2 (6S_ML_SS) and 2-1 (6S_SL_SS), and scenarios 2-2 (6S_ML_FS) and 2-3 (6S_SL_FS).

Experiment B. Impact of staffing arrangement

In this experiment, how different service staffing arrangements (one cashier and a dedicated runner serve each station vs one cashier serves each station with a shared runner for every three cashiers) impact the average waiting time can be analyzed by changing the service time. This can be observed though the pairwise comparisons of scenario 1(4S_SL_FS) and 1-2 (4S_SL_SS), scenario 1-1 (4S_ML_FS) and 1-3 (4S_ML_SS), scenario 2 (6S_ML_SS) and 2-2 (6S_ML_FS), scenario 2-1 (6S_SL_SS) and 2-3 (6S_SL_FS).

Experiment C. Impact of number of service stations

Experiment C investigates how different numbers of servers impact the waiting time and can be analyzed by comparing Model 1 and Model 2 under the condition of the same queuing design and service time, while changing number of service stations. This can be observed though the pairwise comparisons of scenarios 1 (4S_SL_FS) and 2-3 (6S_SL_FS), scenarios 1-1

(4S_ML_FS) and 2-2 (6S_ML_FS), scenarios 1-2 (4S_SL_SS) and 2-1 (6S_SL_SS), scenarios 1-3 (4S_ML_SS) and 2 (6S_ML_SS).

Table 4.2 List of scenarios with Extended Model

Scenario #	Model Name	Change to Base Model
3	*4S_SL_Cp1*	*Extended Model 1: Four stations with an segmented cup drink station (capacity=1), service time of one cashier and one runner serve each station, side queue exit, used percentage of cup drink orders from concession stand 41*
3-1-1	4S_SL_Cp2	Change Extended Model 1 with capacity of cup drink station changed from 1 to 2
3-1-2	4S_SL_Cp3	Change Extended Model 1 with capacity of cup drink station changed from 1 to 3
3-1-3	4S_SL_Cp4	Change Extended Model 1 with capacity of cup drink station changed from 1 to 3
3-2	4S_ML_MCp1	Change Extended Model 1, used cup drink composition of the combined orders of both stations, change side queue exit to middle queue exit
3-2-1	4S_ML_MCp2	Change scenario 3-2 with capacity of cup drink station changed from 1 to 2
3-2-2	4S_ML_MCp3	Change scenario 3-2 with capacity of cup drink station changed from 1 to 3
3-2-3	4S_ML_MCp4	Change scenario 3-2 with capacity of cup drink station changed from 1 to 4
4	*6S_ML_Cp1*	*Extended Model 2: Six stations with an segmented cup drink station (capacity=1), service time of one cashier serve one station with a shared runner, middle queue exit, used percentage of cup drink orders from concession stand 39*
4-1-1	6S_ML_Cp2	Change Extended Model 2 with capacity of cup drink station changed from 1 to 2
4-1-2	6S_ML_Cp3	Change Extended Model 2 with capacity of cup drink station changed from 1 to 3
4-1-3	6S_ML_Cp4	Change Extended Model 2 with capacity of cup drink station changed from 1 to 4
4-2	6S_ML_MCp1	Change Extended Model 2, used cup drink composition of the combined orders of both stations
4-2-1	6S_ML_MCp2	Change scenario 4-2 with capacity of cup drink station changed from 1 to 2
4-2-2	6S_ML_MCp3	Change scenario 4-2 with capacity of cup drink station changed from 1 to 3
4-2-3	6S_ML_MCp4	Change scenario 4-2 with capacity of cup drink station changed from 1 to 4

Experiment D. Impact of combination of servers and service time

Experiment D looks into how the combination of number of servers and service time impacts the waiting time and can be analyzed by comparing in model 1 and model 2 under the condition of same queue design. This can be observed though the pairwise comparisons of scenarios 1 (4S_SL_FS) and 2-1 (6S_SL_SS), scenarios 1-1 (4S_ML_FS) and 2 (6S_ML_SS).

Experiment E. Impact of segmenting cup drink filling process

Experiment E is performed to analyze if adding a cup drink self-service station would reduce the time in system, the difference of average waiting time and maximum waiting time from the comparison of scenarios 1(4S_SL_FS), 3 (4S_SL_Cp1), 3-1-1(4S_SL_Cp2), 3-1-2(4S_SL_Cp3) and 3-1-3 (4S_SL_Cp4) for the four station model, and compare output of scenarios 2 (6S_ML_SS), 4 (6S_ML_Cp1), 4-1-1(6S_ML_Cp2), 4-1-2(6S_ML_Cp3),,4-1-3 (6S_ML_Cp4), for the six station model. To explore which operation configuration will benefit most from cup drink filling process, we can compare the result of scenarios 3-2 (4S_ML_MCp1) and 4-2 (6S_ML_MCp1), 3-2-1 (4S_ML_MCp2) and 4-2-1 (6S_ML_MCp2), 3-2-2 (4S_ML_MCp3) and 4-2-2(6S_ML_MCp3), 3-2-3 (4S_ML_MCp4) and 4-2-3 (6S_ML_MCp4).

4.2 Output Analysis

Each scenario is replicated 100 times in each experiment and the results are presented as the mean of Average Time in System (TIS) and the mean of Max TIS, along with 90% confidence interval for the scenarios of the Models, shown in Table 4.3.

Table 4.3 Results of scenarios with Base Model (in minutes)

Scenario #	Model Name	Avg. TIS (mean)	90% C.I. Avg. TIS	Max TIS (mean)	90% C.I. Max TIS
1	4S_SL_FS	2.61	(2.45,2.77)	8.81	(8.36,9.26)
1-1	4S_ML_FS	2.21	(2.07,2.35)	7.86	(7.4,8.32)
1-2	4S_SL_SS	12.75	(12.1,13.4)	22.91	(22.12,23.7)
1-3	4S_ML_SS	11	(10.43,11.73)	21.2	(20.36,21.96)
2	6S_ML_SS	1.4	(1.29,1.43)	5.0	(4.73,5.29)
2-1	6S_SL_SS	1.5	(1.42,1.56)	5.5	(5.16,5.74)
2-2	6S_ML_FS	0.76	(0.75,0.77)	2.42	(2.27,2.57)
2-3	6S_SL_FS	0.95	(0.93,0.97)	3.44	(3.31,3.57)

4.2.1 Impact of queue layout.

By comparing the output of scenarios 1 (4S_SL_FS) and 1-1 (4S_ML_FS), scenarios 1-2 (4S_SL_SS) and 1-3 (4S_ML_SS), scenarios 2 (6S_ML_SS) and 2-1 (6S_SL_SS), and scenarios 2-2 (6S_ML_FS) and 2-3 (6S_SL_FS), as shown in Table 4.3, the result shows that there is a clear reduction using middle queue exit in both Average Waiting Time and Maximum Waiting Time between a side queue exit and middle queue exit configuration in all pairwise comparisons except scenarios 2 and 2-1.For example, comparing scenarios 1 (4S_SL_FS) and 1-1 (4S_ML_FS), there is no overlap between confidence interval for Avg TIS and Max TIS in both scenarios. On the other hand, there is a small overlap between confidence interval for Avg TIS and Max TIS in scenarios 2 and 2-1, this may be due to the slow service time and long walking distance limiting the effect of queue design. As shown in Figure 4.1, the difference of Average TIS is very small. So we can conclude that although the queue layout will impact the waiting time, in practice, it does not have a major effect on waiting time.

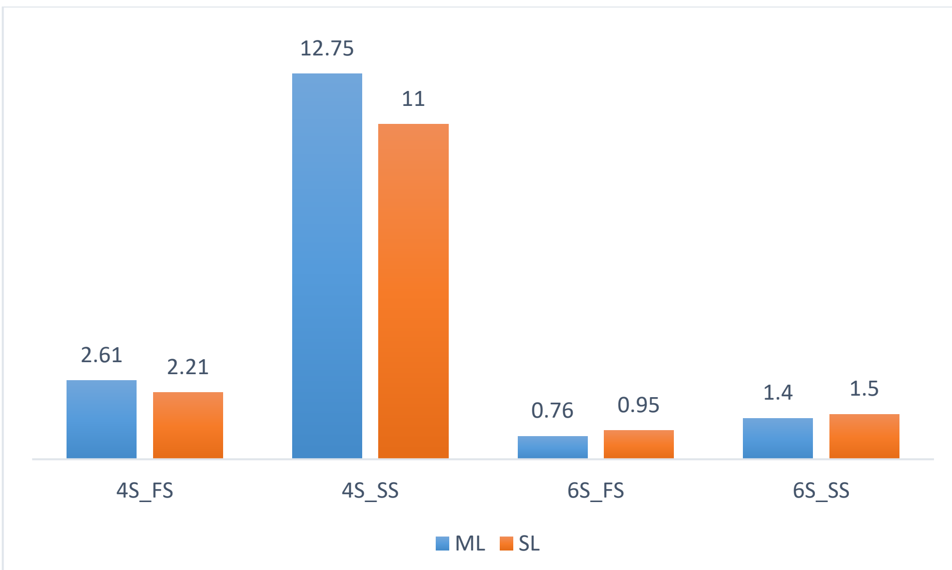


Figure 4.1 Comparison of Avg. TIS for queue layout (in minutes)

4.2.2 Impact of staffing assignments

Pairwise comparisons of the output of scenario 1 (4S_SL_FS) and 1-2 (4S_SL_SS), scenario 1-1 (4S_ML_FS) and 1-3 (4S_ML_SS), scenario 2 (6S_ML_SS) and 2-2 (6S_ML_FS), scenario 2-1 (6S_SL_SS) and 2-3 (6S_SL_FS), as shown in Figure 4.2, the result shows there is a significant difference in both Average TIS and Maximum TIS between different service staffing configurations. Particularly in the four stations model, slower service due to staffing configuration results in a significant increase in the Average Time in System from 2.21 to 11 minutes if the cashier has no dedicated runner. The slower service time will dramatically increase the TIS. For the 6 service station, adding 4 more runners will reduce the Average Time in System in half, from 1.4 to 0.76 minutes, and reduce the Max TIS from 5 minutes to 2.42 minutes.

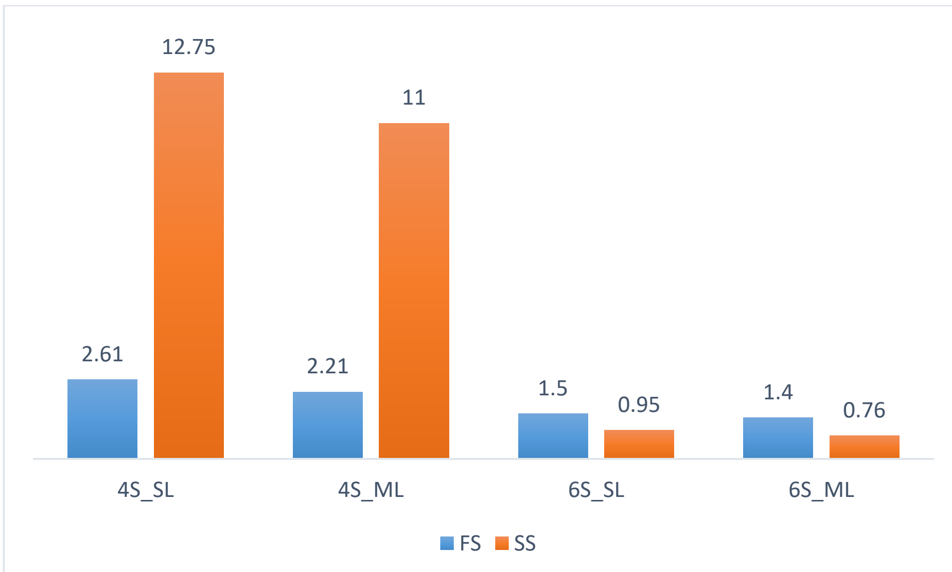


Figure 4.2 Comparison of Avg. TIS for Staffing Configuration (in minutes)

4.2.3 Impact of number of service stations

Comparing scenarios 1 (4S_SL_FS) and 2-3 (6S_SL_FS), scenarios 1-1 (4S_ML_FS) and 2-2 (6S_ML_FS), scenarios 1-2 (4S_SL_SS) and 2-1 (6S_SL_SS), scenarios 1-3 (4S_ML_SS) and 2 (6S_ML_SS), the result shows that there is a significant difference of both Average Time in System and Maximum Time in System between four stations concession stands and six concession stations stands. As shown in Figure 4.3, overall the average TIS of 6 stations are lower than that of 4 stations, especially when there is no dedicated runner for the cashier, adding two more stations will dramatically reduce the waiting time from more than 11 minutes, shown in 4S_ML_SS and 4S_SL_SS, to less than 2 minutes, shown in 6S_ML_SS and 6S_SL_SS.

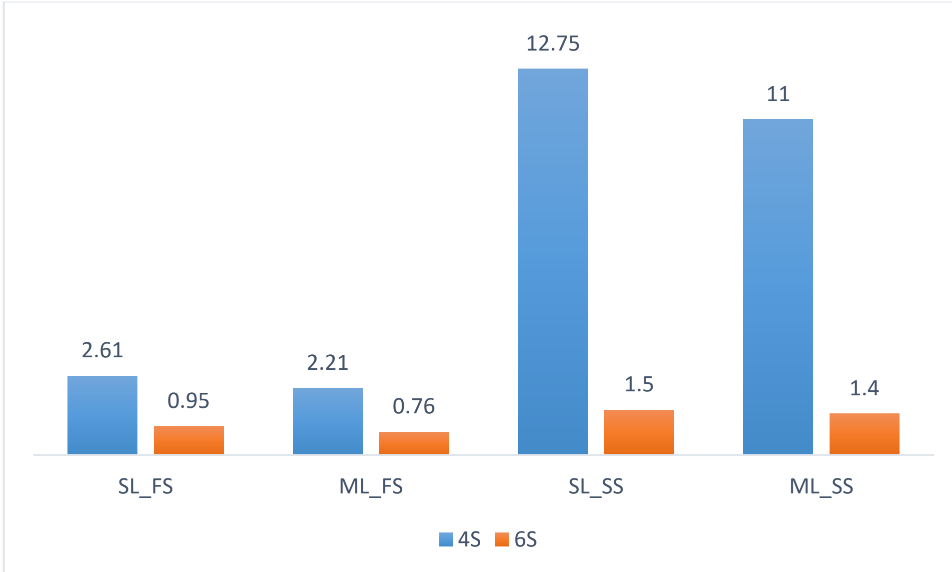


Figure 4.3 Comparison of Avg. TIS for number of service stations (in minutes)

4.2.4 Impact of combination of number of service stations and service time

Comparing scenarios 1 (4S_SL_FS) and 2-1 (6S_SL_SS), scenarios 1-1 (4S_ML_FS) and 2 (6S_ML_SS), as shown in Table 4.4, it can be seen that the 6 station model, with one casher and a shared server, even though it has slower service speed, the Average Time in System is significant less than the 4 station model. This is due to the fact that even when number of stations is increased by 50%, from 4 to 6, the service time does by the same rate, as the service time of 6 station model (one casher with shared runner) is 52.3 and that of 4 station model (one casher with dedicated runner) is 39.7, the service time only increased 25%. Thus, if only 8 employees can be assigned as front workers, 6 Stations with shared server performed better than 4 stations with dedicated server as it has less TIS and max TIS.

Table 4.4 Comparison of TIS for service time and number of stations (in minutes)

Queue	Avg. TIS		Max TIS	
	4S_FS	6S_SS	4S_FS	6S_SS
SL	2.61	1.5	8.81	5.5
ML	2.21	1.4	7.86	5

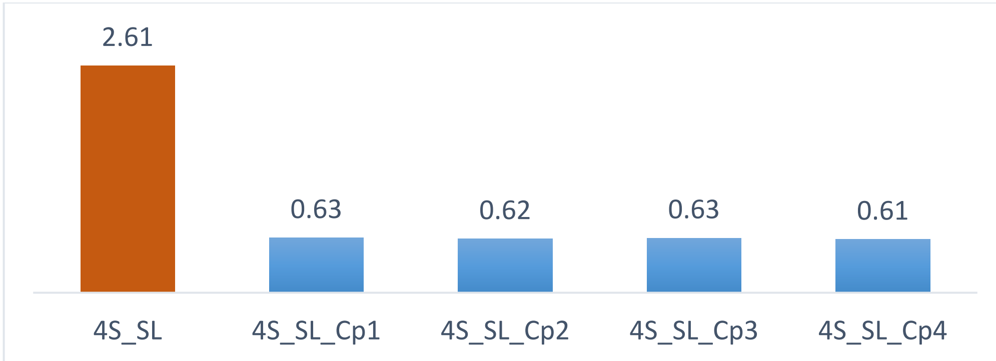
4.2.5 Impact of segmenting cup drink filling process

Since the Extended Model separated the cup drink filling process, the customer who order cup drinks and those who do not order cup drink orders have different routes. Thus, it will be more valuable to analyze the time in system for customers who have cup drink orders and customers who do not order cup drink separately. The result of Average TIS and Max TIS for customers with cup drink orders and customers without cup drink orders is shown in Table 4.5.The CpTIS represents the customers with cup drink orders and noCpTIS represents customers without cup drink orders.

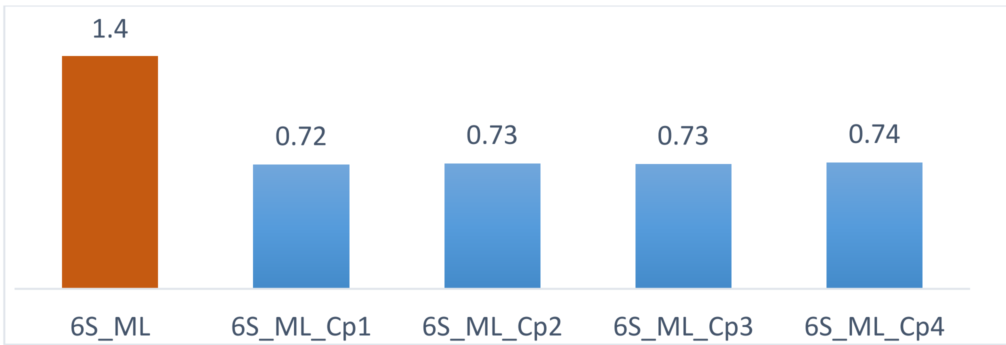
Table 4.5 Results of scenarios with Extended Model (in minutes)

Scenario #	Model Name	Avg. CpTIS	Max CpTIS	Avg. noCpTIS	Max noCpTIS
3	4S_SL_Cp1	35.08	63.82	0.63	2.36
3-1-1	4S_SL_Cp2	2.18	6.55	0.62	2.31
3-1-2	4S_SL_Cp3	1.27	3.40	0.63	2.30
3-1-3	4S_SL_Cp4	1.21	3.36	0.61	2.27
3-2	4S_ML_MCp1	27.07	47.56	0.59	2.22
3-2-1	4S_ML_MCp2	1.53	4.41	0.57	2.29
3-2-2	4S_ML_MCp3	1.20	3.15	0.57	2.28
3-2-3	4S_ML_MCp4	1.18	3.15	0.58	2.26
4	6S_ML_Cp1	14.93	25.43	0.72	2.24
4-1-1	6S_ML_Cp2	1.47	3.50	0.73	2.33
4-1-2	6S_ML_Cp3	1.34	2.99	0.73	2.25
4-1-3	6S_ML_Cp4	1.34	2.97	0.74	2.35
4-2	6S_ML_MCp1	27.73	48.22	0.73	2.22
4-2-1	6S_ML_MCp2	1.78	4.65	0.73	2.25
4-2-2	6S_ML_MCp3	1.36	3.04	0.73	2.19
4-2-3	6S_ML_MCp4	1.34	3.07	0.73	2.14

Overall the waiting time for customers without cup drink orders is close in all of the scenarios, the average TIS is approximately 0.6 minutes and the maximum TIS is approximately 2.3 minutes, comparing with the average TIS of 2.61 and Max TIS of 8.81 in Model 1, as shown in Figure 4.4 (a), and average TIS of 1.4 and max TIS of 5 in Model 2, as shown in Figure 4.4 (b). Thus, the waiting time for customers without cup drink orders reduced dramatically.



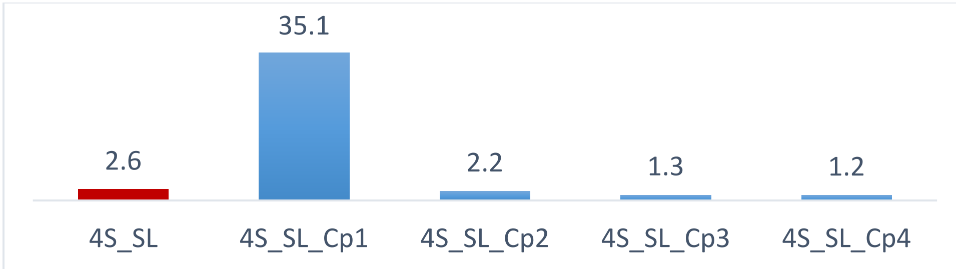
(a)



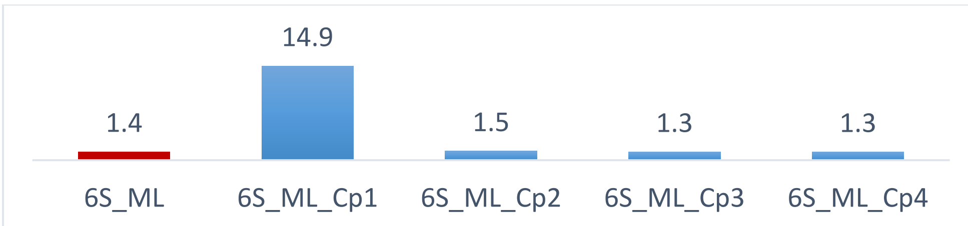
(b)

Figure 4.4 Comparison of Avg. TIS for Customers with no Cup Drink Orders (in minutes)

Through the comparison of scenarios 1, 3, 3-1-1, 3-1-2 and 3-1-3 for 4 station model, as shown in Figure 4.4 (a) and the output of scenarios 2, 4, 4-1-1, 4-1-2, 4-1-3 for 6 station model, as shown in Figure 4.4 (b), the benefit of adding additional cup drink stations that separate the cup drink filling process for customers with cup drink orders is significant, as long as the capacity of cup drink station is more than one. If there is only one cup drink station, the average TIS for customers with cup drink orders will be more than 15 minutes, as shown in scenarios 3 and 4, the average waiting time is 35 minutes in scenario 1 and 15 minutes in scenario 4.Adding a second self-service station dramatically reduced the TIS for customers with cup drink orders. For example, for the 4 station model, two self-service cup drink stations can reduce the avg. TIS from 35 minutes to 2.18 minutes, adding a third self-service station can reduce the avg. TIS to 1.27 minutes. However, adding a third or fourth cup drink station will not make significant difference on Time in System. For example, for the 4 station model, adding a fourth cup drink machine will only reduce 0.06 minutes from 1.27 minutes.



(a) 4 Station Model



(b) 6 Station Model

Figure 4.5 Comparison of Avg. TIS for Customers with Cup Drink Orders (in minutes)

In addition, by separating the cup drink filling process, the avg. TIS of 4 station model (4 service stations with a cashier and dedicated runner) is a little shorter than the avg. TIS of 6 station model (6 service stations with a cashier and shared runner), as shown in Table 4.6, the avg. TIS in column of 4S is slightly smaller than the time in column of 6S, which is an opposite result to experiment D, which shows 6S model is better than 4S model.

Table 4.6 Comparison of TIS for number of stations in Extended Model (in minutes)

Variables	**Avg. TIS**		**Max TIS**	
	4S	**6S**	**4S**	**6S**
ML_MCp1	27.07	27.73	47.56	48.22
ML_MCp2	1.53	1.78	4.41	4.65
ML_MCp3	1.2	1.36	3.15	3.04
ML_MCp4	1.18	1.34	3.15	3.07

Chapter 5 Conclusion and Future Work

This chapter first summarizes the results from input analysis and experiment output analysis, then discuss the application of those results, finally addresses the limitations of this study and the future work that can be done to further improve the concessions customer waiting time.

5.1 Summary

This research investigates the impact of queue layout, staffing configuration and number of serving stations based on actual data from football stadium concessions operation during game days. The simulation study performed shows that:

a) The peak time of customer arrival for food purchase is 30-60 minutes before game starts and a second peak time is about 30 minutes after game starts. The valley is 15 minutes before and after kickoff.
b) The staffing configuration and number of serving stations make a significant difference on Time in System.
c) Two people (a cashier with a dedicated runner) serving one station can be about 12 seconds on average faster than a cashier with a shared runner serving multiple stations.
d) Model 2 (6 service stations with a shared runner) exhibits a smaller average TIS than Model 1 (4 service stations with dedicated runner)
e) A middle queue exit results in a slightly shorter average TIS than side queue exit but the difference is not significant.
f) Separating the cup drink filling process from checkout process will reduce the average time in system for customers without cup drink orders, and will reduce the average time in system for customers with cup drink orders only if there are more than one cup drink filling stations. Having only one cup drink machine will dramatically increase the TIS for customers with cup drink orders, adding a second cup drink machine will reduce the avg. TIS to approximately 2 minutes, but adding a third machine and fourth machine will not significantly reduce the TIS.

As the service time includes customer order time (customer decided), food and drink retrieval time (staffing configuration decided), drink filling time, and check out time (POS machine processing time), any lag in those process will result in additional Time in System. To avoid a long Time in System, all the machines and equipment should be tested to ensure the functionality and in time supply, the workers need to be trained appropriately with optimized work flow to ensure the service efficiency. Moreover, if a group of workers is inexperienced or work efficiency is low, then adding more service stations (registers) and staff is necessary. On the other hand, if there are only 4 service stations or 4 POS machines, the service efficiency is extremely important, and each station should have one cashier and a dedicated runner to serve customers. If the staffing is limited but a new register can be added, then having more registers open with shared runners is more efficient in reducing Time in System than having a runner and a cashier at each station.

5.2 Limitation of this research and Future work

This study has developed models to research the factors that impact waiting time, however, there are some limitations of sample size and simplifications of actual operation process when developing those models. Future work can be performed to provide more comprehensive guidance on reducing customer waiting time at stadium concessions.

1. Customer arrival rate is fixed and generated from a limited number of events for this study. Exploring the customer arrival rate at different concession stands and different games will help understand traffic flow and the requirement for number of servers for each concessions stands.

2. The service time dataset is limited. This study only has service times for two concession stands at different games and we assume the difference of service time is from the number of workers per stands, rather than staffing configurations. The service time of other concessions stands can be collected to understand how the differences in staffing configuration impact the service time and identify the bottlenecks of service time.

3. This research only focused on front end operations in the concession stand. The back end operation including facility layout and staffing will also impact the Time in System. Value Stream Mapping can be used to identify the waste and speed up opportunities.

4. This study did not consider balking or reneging. In actual scenario, the customer may leave the line (reneging) or do not enter into the line when the length of line is long (balking). However, because it is difficult to capture the customer does not join the line, and customer who

leaves the line is negligible based on game day observations, the balking or reneging behavior is not considered in this simulation model, it may result in longer Time in System and larger number in system than actual data under scenarios analysis.

5. An important and interesting addition to this study would be to include the cost of labor as a factor to optimize with customer TIS.

6. Both concession stands in this study service the same customer demographics with faculty, season ticket holders, and opponent’s fans eating. There might be different areas of the stadium that have students, scholarship donors, alumni seating where orders and arrivals are different.

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Appendices

A. IRB Documentation of Consent – Video Release Form

VIDEO RELEASE

During your participation in this research study, "Concessions customer waiting time improvement project", you will be videotaped. Your signature on the Informed Consent gives us permission to do so.

Your signature on this document gives us permission to use the videotape(s) for the additional purposes of *publication and training* beyond the immediate needs of this study. These videotapes will not be destroyed at the end of this research but will be retained *indefinitely*.

In addition, the following persons or groups will have access to the tapes:

Auburn University Athletics IT Department, Aramark management team at Auburn

Your permission:

I give my permission for videotapes produced in the study , "Concessions customer waiting time improvement project**" to be used for the purposes listed above, and to also be retained *indefinitely*.**

______________________________ ______________________________

Participant's Signature Date Investigator's Signature Date

______________________________ ______________________________

Participant's Printed Name Investigator's Printed Name

B. IRB Documentation of Consent – Informed Consent Form

INFORMED CONSENT

for a Research Study entitled

"Concession Customer Waiting Time Improvement Project"

You are invited to participate in a research study to optimize layout and queuing system for concessions operation. The study is being conducted by Mengdie Chen, Graduate Assistant, under the direction of Gregory Harris in the Auburn University Department of Industrial and Systems Engineering. You were selected as a possible participant because you are an operator at concessions and are age 19 or older.

What will be involved if you participate? If you decide to participate in this research study, you will be asked to work as usual with a camera inside and outside concessions. Your total time commitment will be approximately 3 hours.

Are there any risks or discomforts? The risks associated with participating in this study are losing control of personal image if cameras are missing, and potential stress under videotaping. To minimize these risks, we will stay with cameras all the time and have encrypted SD card in camera, and will stop videotaping if anyone feels uncomfortable.

If you change your mind about participating, you can withdraw at any time during the study. Your participation is completely voluntary. If you choose to withdraw, your data can be withdrawn as long as it is identifiable. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the Department of Athletics or Aramark.

Your privacy will be protected. Any information obtained in connection with this study will remain anonymous (or confidential). Information obtained through your participation may be published in a professional journal or presented at a professional meeting.

If you have questions about this study, please ask them now or contact Mengdie Chen, Graduate assistant at Auburn University, email address: mzc0088@auburn.edu or Gregory Harris, Professor at Auburn University, email address: greg.harris@auburn.edu. A copy of this document will be given to you to keep.

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334)-844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

HAVING READ THE INFORMATION PROVIDED, YOU MUST DECIDE WHETHER OR NOT YOU WISH TO PARTICIPATE IN THIS RESEARCH STUDY. YOUR SIGNATURE INDICATES YOUR WILLINGNESS TO PARTICIPATE.

______________________________ ______________________________

Participant's signature Date Investigator obtaining consent Date

______________________________ ______________________________

Printed Name Printed Name

Participant's initials ______