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Evaluating the Effect of Smart Parking Technology on Campus Parking System Efficiency using Discrete Event Simulation

Glenn Phillip Surpris
Embry-Riddle Aeronautical University - Daytona Beach

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Glenn Phillip Surpris

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Abstract

Author: Glenn Phillip Surpris

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This study was conducted to investigate the effect of smart parking systems (SPS) on parking search times (PST) in large parking lots. SPSs are systems that disseminate real-time parking spot availability to drivers searching for parking. The literature review revealed discrete event simulation (DES) to be a suitable tool for studying the dynamic behavior in parking lots. The parking lot selected for data collection was a university parking lot with 234 spaces. The data collected included arrival rates, departure rates, the geometric properties of the parking lot, preferred parking search strategies, and driving speeds. Arena 13.9, by Rockwell Automation, Inc, was selected as the modeling software. The base model was built from observed parking search strategies (PSS) of drivers. The model was validated using a *t*-test for independent samples to compare the PSTs of the base model and actual parking lot. Once the base model was verified and validated, the logic was altered to reflect (PSS) (IV) with real-time parking availability (i.e. simulating the presence of an SPS). The PSTs (DV) for the base and experimental models were compared using a *t*-test for independent samples. It was found that SPSs reduce PSTs by an average of 11 seconds. This shows great potential for a multi-lot SPS that might save a larger amount of time and harmful vehicle emissions.

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This thesis was prepared under the direction of the candidate's thesis committee chair, Dahai Liu, Ph.D., Department of Human Factors and Systems, and has been approved by the members of the thesis committee. It was submitted to the Department of Human Factors and Systems and has been accepted in partial fulfillment of the requirements for the degree of Master of Science in Human Factors and Systems.

THESIS COMMITTEE:

Dahai Liu, Ph.D., Chair

Albert Boquet, Ph.D., Member

Massoud Bazargan, Ph.D., Member

MS HFS Program Coordinator

Department Chair, Department of Human Factors and Systems

Associate Vice President for Academics

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List of Abbreviations

Abbreviation	Meaning
SPS	**S**mart **P**arking **S**ystem
PST	**P**arking **S**earch **T**ime
DES	**D**iscrete **E**vent **S**imulation
SPARK	**S**mart **Park**ing
VANET	**V**ehicular **A**d-hoc **Net**work
TA	**T**rusted **A**uthority
RSU	**R**oad-**S**ide **U**nit
OBU	**O**n-**B**oard **U**nit
SME	**S**ubject **M**atter **E**xpert
ERAU	**E**mbry **R**iddle **A**eronautical **U**niversity
PSS	**P**arking **S**earch **S**trategy
WT	**W**ait **T**ime

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Introduction

One characteristic of an advanced civilization is its ability to transport large amounts of people and resources in a logical, efficient, and expedient manner. Any community must have the proper technology and infrastructure (e.g. automobiles, roadways, railways, and airports) to facilitate the flow of its members and resources with respect to the needs of that community. Parking facilities are a necessary component of any transportation system to store vehicles when they are not in use. However, as parking facilities grow large, advanced methods of parking management are needed to reduce inefficiencies in finding available parking spaces. Smart parking systems (SPS) have arisen in high density population areas to help patrons easily find parking in a crowded facility. This study seeks to evaluate the usage of SPSs on university parking search times (PST), a valuable parking facility performance characteristic, using discrete event simulation (DES).

Parking

Nature of parking systems.

This section will describe the nature of parking lots, the planning that occurs in the design of parking lots, and some of the variables by which parking lots may be measured. Parking lots, for the purposes of this study, are defined as designated land spaces for the storage of motor vehicles. Parking lots usually accompany buildings that house members of institutions (e.g. schools, churches) or organizations (e.g. business establishments) that operate motor vehicles. These plots of land can have capacities ranging from a few vehicles to hundreds of vehicles. Lots are normally paved and have paint marks that outline the space designated for each vehicle. Parking spots are normally arranged in rows, and aisles provide access to the spaces in each row. The lots also have defined exit and entrance points.

Careful planning goes into the development of parking facilities. Many design factors must be considered before a parking facility is built, including the number of vehicles that must be accommodated, the space that each vehicle needs, the total allocated parking lot space, and the alternative parking layouts and patterns. After these design factors are identified, the layout that efficiently utilizes space requirements must be selected. The best layout would ideally maximize capacity while minimizing patron inconvenience (Tompkins, White, Bozer, & Tanchoco, 2003). Factors affecting patron inconvenience are PSTs, park and de-park times, and walking distance from the parking facilities to final destinations. The interaction between patron inconvenience factors and design factors is complex and must be optimized. For example, park and de-park times are directly affected by the size of the parking space relative to the patron's vehicle. As parking spaces increase in size, less time is needed to park correctly. However, large spaces decrease the overall capacity of a parking lot. Parking spaces cannot be too large or too small.

Parking systems can be further classified by a number of different variables such as location (i.e. on or off street), size, the types of vehicles accommodated, elevation (i.e. underground, surface, or elevated garage parking), and intended patronage (e.g. employee, student, resident). In addition to the previously stated factors of patron inconvenience, parking systems are generally evaluated on their maximum capacity, the average time it takes to enter and exit the parking facility, queue lengths at various points within the system, and how well traffic flows within the parking system (e.g. how many average disruptions in flow occur within the system).

University parking challenges.

University campuses are expansive landscapes where, depending on size, hundreds to thousands of faculty, staff, and students gather throughout the year to pursue educational endeavors. Many universities have parking restrictions for undergraduate students, especially first year students. This is to help alleviate the demand on the parking facilities. Commuter campuses, in lieu of residential buildings, have larger parking facilities to accommodate its patrons who are more likely to own motor vehicles. This can include above and below ground parking garage structures. Regardless of campus type, university campuses have suitable parking facilities for the application of an SPS. This is because as parking systems grow larger, the ability of a motorist to physically see where available parking is decreases.

As a push for campus expansions and improvements is made prevalent around the country, university administrators are facing increasing student enrollment and an ever increasing demand on limited parking space. For example, at Embry-Riddle Aeronautical University in Daytona Beach, FL, new building and facility developments, aimed at increasing both the quality of student life and student enrollment, seem to put added stress on current parking facilities, based on observation. Brown-West (1996) cites several factors (e.g. local building regulations, lack of funding priority, and institutional policies affecting land usage) that administrators must simultaneously manage while trying to improve parking facilities. An optimization model was developed that produces the ideal parking arrangement (e.g. parking stall width and angle, aisle width) based on inputs such as the supply of existing parking, the projected parking demand, and legal and financial factors. The model was constrained by the types of vehicles, users, available space, and local regulations. One of the main findings of the study was that angled parking (i.e. less than 90 degrees) can accommodate more vehicles. While this seems as if it would reduce PSTs by increasing the number of available spaces, Brown-West (1996) recommends that angled parking be avoided as it generally increases disruptions of traffic flow.

The parking challenges at university campuses can be further realized by noting the studies that seek to alleviate them. For example Fries, Chowdury, Dunning, and Gahrooei (2010) conducted a study to evaluate how disseminated real parking information affects the travel time, delays, and varying amounts of congestion that accompany a university with over 17,500 enrolled students and 100,000 visitors that attend sporting events. Another problem universities face is determining how to divide its available parking resources among faculty, staff and students. Harris and Dessouky (1997) used simulation to optimize the parking divisions at a major university. The authors were able to demonstrate that universities often have trouble dividing parking resources amongst faculty, staff, and students in an optimal manner.

Overall, universities face problems both in the planning of future parking facilities and the management of current ones. During the planning process, universities must account for projected parking demand, building regulations, and funding constraints. These affect the characteristics of the parking structure to be built. In the management of current facilities, universities must find ways to reduce delays, travel times, and congestion for all three types (i.e. faculty, commuters, and resident students) of its patrons.

As parking facilities grow larger and demand increases for parking, systems to help drivers find available parking become necessary to better manage the time and resource costs associated with the process of parking. These SPSs are able to monitor parking space usage and direct drivers to available spaces. The primary method of collecting usage information has come in the form of sensors at entrances and exits or sensors at individual parking spaces. Several methods of disseminating availability information have been developed such as variable message signs and mobile/internet interfaces (Maccubbin, 2000; Lu, Lin, Zhu, and Shen, 2009).

Goal of This Study

The goal of this study was to use DES to investigate the effect of an SPS configuration on the PST within a university parking lot. Data collected on arrival rates, parking durations, distances between spaces, departure rates from areas in the lot, and driving speeds were used to build a DES model in Arena. Once the model was validated, the logic was altered to experiment with the application of an SPS. The average PST of the two models was compared.

Literature Review

An SPS was defined, for the purposes of this study, as any system that actively monitors parking space occupancy and makes that information available to drivers who are searching for empty spaces. The next section describes some of the technology (both implemented and proposed) used in smart parking systems. It is worth noting that smart parking systems are also usually able to alert drivers of stolen vehicles, offer streamlined payment options, and/or allow for advanced parking spot reservations. Those performance aspects of smart parking systems were not the focus of this study.

Smart Parking Technology

Chinrungrueng and Sunantachaikul (2007) described a proposed SPS that utilizes optical wireless sensors as its base technology for detecting the movement of vehicles and space occupancy. The authors solved the problem of false positives caused by pedestrians and other non-vehicular bodies by installing two optical heads, spaced apart, connected to one sensor. In this manner, the optical heads work together to judge the size of the passing object. Only those disturbances fitting the size of a motor vehicle trigger the sensor to register the presence of the vehicle.

Yan-Zhong, Li-Min, Hong-Song, Ting-Xin, and Zheng-Jun (2006) developed an SPS that utilizes individual sensors for every parking space. These sensors are connected to a wireless network to inform drivers of a lot's real-time capacity and the location of empty spots. Sensors are deployed at every parking space and monitor the space's occupancy. This information is dispersed to the sink node that collects the information and relays it to a management station. The management system sends out the information to a sign at the entrance informing drivers of the parking utilization. It also updates the appropriate guiding nodes located at every major intersection. These guide nodes direct drivers toward available parking.

Of special interest is the scheme for managing parking spaces devised by Yan-Zhong et al. (2006). It can be tedious and confusing to have guidance nodes for every parking spot. In this scheme, the parking spaces are grouped into small areas. The guiding nodes do not direct drivers to individual spots, but rather, they guide drivers to parking areas with unused capacity. This is an efficient scheme and is depicted in Figure 1. However, the technology (e.g. sensors, routing protocol) is not perfect based on preliminary experiments conducted by Yan-Zhong et al. (2006). Improved methods for improving data transfer reliability, among other issues, are recommended by

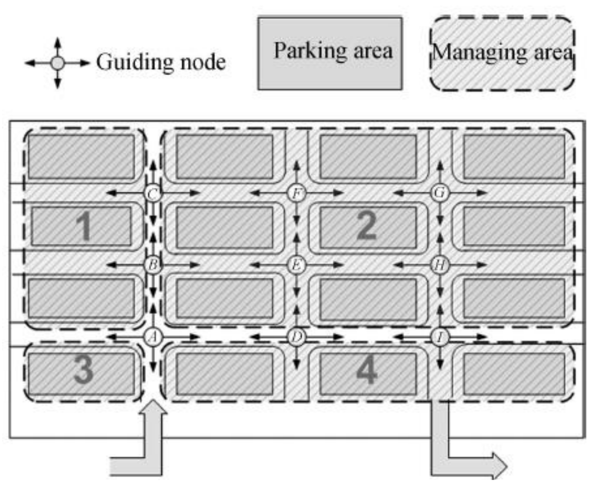

Figure 1. Parking management system using guiding nodes and grouped parking spaces. Adapted from "A Parking Management System Based on Wireless Sensor Network," by Yan-Zhong, B., Li-Mun, S., Hong-Song, Z., Ting-Xin, Y., & Zheng-Jun, L. 2006, *Acta Automatica Sinica, 32(6)*, p. 973.

the authors for further testing.

Lu et al. (2009) published a paper on a smart parking scheme for large parking lots called SPARK (i.e. **S**mart **Park**ing). The scheme uses a vehicular ad hoc network (VANET) to disseminate real-time parking information and provide parking navigation. A VANET is a communication system in which vehicles communicate with each other and roadside infrastructure. The components of the SPARK system are as follows: a trusted authority (TA), three roadside units (RSUs), wireless onboard units (OBUs) for each vehicle, and parking spaces. RSUs are placed in a perimeter around the affected parking lot. A diagram of the setup is shown in Figure 2. Each vehicle that is part of the system is equipped with an OBU. The RSUs are wireless devices capable of communicating with the OBUs as they enter within range of the RSUs. The TA (not pictured) is present for security reasons. The identification (ID) code of the OBU is kept secret with a temporary ID generated and assigned by the TA. The ID of the OBU is only available, through the TA, after an exceptional event such as a crime.

The parking spaces are resources with specific locations (x_i, y_i) that the RSUs have inventoried. As OBUs enter smart parking lot, an encryption process takes place with the TA, the OBU, and the RSUs. The OBU then requests a parking space that fits given parameters dictated by the driver's preferences. The RSUs locate an available space, and by

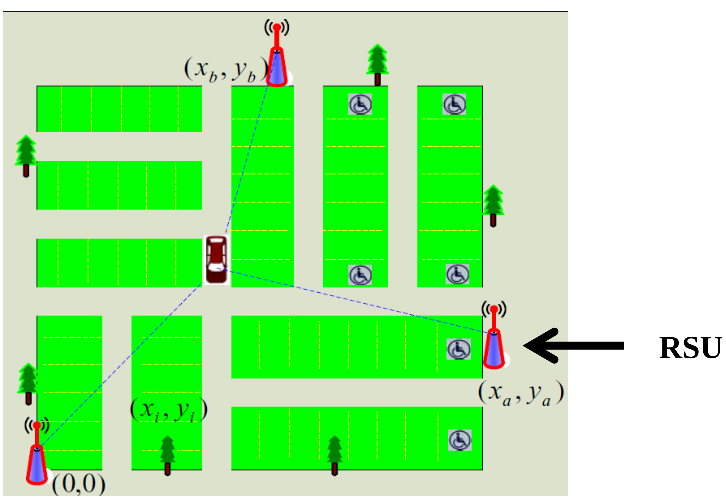

Figure 2. SPARK model diagram showing RSUs communicating with an OBU-equipped vehicle. Adapted from "SPARK: A New VANET-based Smart Parking Scheme for Large Parking Lots," by R. Lu, X. Lin, H. Zhu, and X. Shen, 2009, *Proceedings of the IEEE INFOCOM*, p. 1414.

measuring the distances between themselves, the OBU, and the available space, the RSU's provide the OBU with navigational instructions for the shortest path to the parking space. Once the vehicle parks and is powered off, the OBU goes into a low-power state in which it sends out an intermittent beacon to the RSUs. It is in this manner the RSUs keep track of which spaces are occupied. After the vehicle is powered on and proceeds to leave, the OBU sends a streaming signal to the RSUs, updating its location and indicating that the parking space is now available. The OBU then exits the system.

In addition to providing the real-time parking navigation, the RSUs can communicate with OBUs within the RSUs' range, but outside of the parking lot. The RSUs can provide information such as how many spaces are occupied within the parking lot and probability that the OBU will be blocked from finding a space. This probability is computed using the *M/G/c/c* queue model. It is assumed that vehicle arrivals follow a Poisson distribution with λ defined as the rate of vehicle arrival and $E(t)$ defined as the mean parking time in hours. The total number of spaces in the lot is denoted by c. The probability that every space will be occupied is denoted by p_c. Probability B, the probability that the vehicle will not find a space once it arrives in the lot, is equal to p_c. The probability that there are n vehicles in the parking lot is denoted by p_n. Lu et al. (2009), using the *M/G/c/c* queue model, derived the following equation (1) for p_n:

$$p_n = \frac{\rho^n}{n!} \cdot \left[\sum_{i=0}^{c} \frac{\rho^i}{i!}\right]^{-1}, \text{for } n = 0, 1, 2, \dots, c, \tag{1}$$

where $\rho = \lambda \cdot E(t)$. By substituting n for c, probability B(c,p) can be calculated in equation (2)

$$\mathrm{B}(c, \rho) = p_c = \frac{\rho^c}{c!} \cdot \left[\sum_{i=0}^{c} \frac{\rho^i}{i!}\right]^{-1} \tag{2}$$

It is worth noting that as *c* grows large, a recursion algorithm will be used by the RSUs to calculate the blocking probability (Lu et al., 2009). It is assumed that drivers with this information would be able to choose between multiple parking lots for a single facility. These types of parking systems with multiple facilities are usually found in large facilities such as universities and airports. The next section reports some of the recent implementations of smart parking technology in the U.S.

Smart Parking Applications

Parking management professionals of numerous large facilities and locations have investigated SPT as a way to reduce driver frustration, PSTs, and harmful vehicle emissions (Price, 2011). For example, the parking garage at the Dallas/Fort-Worth International Airport uses a parking guidance system to help drivers find free parking spaces (Chinrungrueng and Sunantachaikul, 2007). Loop detectors at key areas determine vehicle occupancy for the given area. This information is transmitted to a central processer where it is complied, manipulated, and sent to display signs that direct drivers to available spaces. Similar systems have been implemented at Baltimore-Washington International (BWI) and Logan International. At BWI, the SPS manages 13,200 spaces (Charette, 2007).

In 2010, the city of San Francisco deployed a federally funded pilot SPS called SF*park*. It is a system that uses sensors to disseminate parking space occupancy to mobile phone and internet users. The system also manipulates metered parking rates in an attempt to direct drivers away from high-traffic areas and into low traffic areas. By the end of the summer of 2011, the SF*park* program will have a total of 9,200 sensor-equipped parking spaces, a good portion of San Francisco's total of ~24,000 metered spaces. (Charette, 2008; SFPark, 2011).

None of these real world applications would work as well as they do without a good understanding of how people search for parking. Having a good understanding of human search behavior allows engineers to predict how human behavior will change once it receives parking availability information. The next section discusses the theory behind parking search behavior and outlines models and experiments designed to explain this behavior.

Parking Search Behavior

When considering introducing any SPS to a parking facility, it is of importance to understand and approximate how the smart parking system will impact actual driver search behavior. This includes developing an understanding of how to accurately model parking search behaviors as they exist without a smart parking system. A number of studies have sought to produce models that predict driver search behavior and parking choice based on a number of variables. These variables include trip departure time, parking costs, walking distance to final destination, previous experience, perceived probability of parking availability, estimated search time, perceived safety and security, and perceived vehicle competition (Caicedo, Robuste, & Lopez-Pita, 2006; Lam, Li, Huang, & Wong, 2005; Martens & Benenson, 2008; Thompson & Richardson, 1998). Most of the models explain parking search behavior in terms of utilities and dis-utilities of discrete choices. These models are discussed in further detail in this section.

Thompson and Richardson (1998) provide two models for parking search behavior: a behavioral logic model and an analytic model. The behavioral model can be found in Figure 3. The behavioral model begins with the beginning of the search, an examination of a parking lot, and an evaluation of the parking lot. If the parking lot is accepted as a suitable choice, the next decision point is whether or not a space is available. If the parking lot is not accepted, the route to the next lot is determined, and the driver proceeds to the next lot to start the examination process over. If the lot is accepted but no space is available, there is a waiting period during which the lot is periodically reevaluated. Once a space becomes available, the driver will park in that space. If the wait becomes too long, the lot is rejected, and the search for a new lot begins.

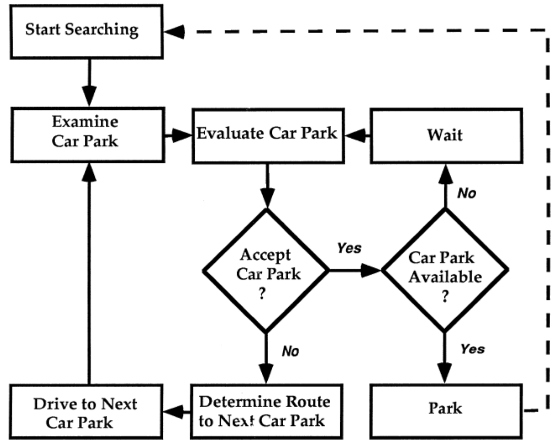

Figure 3. Behavioral parking lot search model. Adapted from "A Parking Search Model," by Thompson, R., & Richardson, A. 1998, *Transportation Research Part A, 32(3)*, p. 160.

The analytical search model developed by Thompson and Richardson (1998) was based on minimizing the parking disutility that arises from three sources: access, native, and waiting costs. Access costs are those associated with traveling to the parking lot and searching for a space, native costs are those associated with parking fees and walking from the lot to the final destination, and waiting costs are those accrued from waiting for a space to be vacated. The authors provide methods of estimating the perceptions of a parking lot, when a driver will stop searching, expected gain from continuing a search, and searching direction.

These methods come in the form of several formulas for each attribute. For example, in order to define under which circumstances a person will continue searching for a parking space (i.e. expected gain from continuing a search), the model utilizes the formula in equation (3):

$$g' > 0 \tag{3}$$

where *g'* is the expected gain in utility. As long as *g'* is above zero, the user will continue to search for parking spaces. *g'* is calculated by the formula (4):

$$g' = \sum_{\forall k \in T} (U_k * p_k) - U_{current} \tag{4}$$

where U_k is the utility of an alternative parking lot k, $U_{current}$ is the utility of the current parking lot, and p_k is the probability of selecting alternate parking lot k. p_k is determined by logit type model. Other formulas are given for items such as determining the direction of search. Thompson and Richardson's model was then run on a hypothetical parking lot. They found that their model predicts that enforcing stricter parking duration limits significantly lowers PST. This is important because strict parking limits increases parking spot turnover. Thus, for any study looking to examine PST, parking spot turnover data should also be collected.

Martens and Benenson (2008) offer a spatially explicit model for predicting driver search behavior and its sensitivity to new parking policies. Spatially explicit models are those that make direct attempts to relate driving parking choice to variables directly related to the spatial characteristics of the available parking choices. The authors stressed developing an on-street/off-street model that represents a real geographic area. The driver search behavior, used for the model, was based on field surveys and the authors' logical thinking. In their simulation runs, Martens and Benenson (2008) demonstrated the capability of the model to assess the impact of the addition of a parking garage to the parking area. They concluded that a new garage would not produce a significant reduction in PST within the studied area, due to characteristics inherent to the city area studied.

Caicedo, Robuste, and Lopez-Pita (2006) used surveys to model parking expectations of patrons of an underground parking facility. Three surveys were used: the first measured the importance of factors in deciding where to park, the second measured the likelihood patrons would wait for a spot in a full lot, and the third measured the probability patrons would exit a line while waiting to get in to a lot. In addition to surveys, the authors observed patron behavior at the lot. These behaviors included arrival rate, departure rate, parking spot turnover, and parking durations. Using these observations and principles of random utility theory, the authors were able to create a probability-based parking search model that was put through a series of simulations under the modified parameters of an SPS. The results demonstrated that PSTs were significantly lower when patrons had knowledge of the locations of available parking spaces.

In summary, the studies on parking search behavior model searching as a process with a goal of minimizing disutility. Disutility arises from inconveniences such as parking costs, walking distance, and parking search times. The weight that each disutility holds can be varied by factors such as parking duration intention and patron category. Actual search behavior can be assessed in many ways, such as administering parking preference surveys, observing actual parking choices, and prioritization of parking areas based on the logic of minimized disutility. The next section describes DES, a viable tool for studying the problems of evaluating the effect of real-time parking information on PST and behavior.

Discrete Event Simulation

DES is a useful tool for systems analysis through the modeling of system changes at discrete intervals in time. It allows for a system to be studied in many aspects of performance, such as throughput, resource utilization, and work completion time. If a system can be described as a series of discrete events, it is likely that it can be modeled using DES. A discrete event is any event that can be observed as occurring at a specific point in time. Thus, change in the overall system only occurs at specific points in time (Kelton, Sadowski, & Swets, 2010). A patron parking in a parking space is a typical discrete event. Parking can be separated from all other events that happen in the parking system and can be defined as occurring at a certain point in time. DES uses a simulation clock that records the time that any event occurs using an event calendar.

DES is a simple analytical solution that is suitable for complex dynamic systems. Systems such as manufacturing plants, emergency facilities, computer networks, theme parks, and parking lots can be modeled with DES (Kelton et al., 2010). DES has several advantages over other methods of modeling (e.g. physical modeling, pure mathematical modeling, and conceptual models) as DES is cost-effective, time-effective, easy to use, and safer than other methods of experimentation.

Randomness must be accounted for when studying any system. An example of this is observing the number of customers that enter a store. The arrival rate of customers varies from day to day. DES accounts for this variability by using probability distributions to describe various system inputs, such as arrival rates. This leads to one important limitation of DES. The output that a DES yields is only an approximation, and is only as accurate as the data that was fed into the DES model. If the data is not accurate, then the results will not be either. Another limitation of DES is that the models are only valid under specific assumptions. Experimenters also need to careful about applying DES models to situations for which they are invalid.

DES study methods.

Law (2006) proposes a structured method for conducting successful simulation studies to minimize these limitations. The first step is to define the problem. This includes defining the objective of the study, the scope of the study, questions that will be answered, and the required time and resources. The next step, Stage 2, is to collect research and data with the intent of making an assumptions document. The layout of the system, the detail of the model, assumptions of the model, performance characteristics of the system, and so forth, are all collected in this stage. The assumptions document is built from this information. Of special note are the performance characteristics as these are essential for validation of the programmed model in stage 5.

Stage 3 involves presenting the assumptions document to a panel of knowledgeable individuals and subject matter experts (SME) to ensure that the document is valid. Any errors in the logic must be updated. Stage 4 involves programming the model with simulation software or a programming language. Stage 5 is an important step that ensures the programmed model is a valid representation of the existing system. This can be verified by comparing the outputs of the existing system from Stage 2 to the results the model yields. SMEs should also review the model for face validity (i.e. ensuring the programmed model output appears reasonable). Finally, a sensitivity analysis should be conducted to see which variables have the most effect on system output. This is done to ensure that careful attention is paid to these variables so that they can be modeled carefully (Law, 2006).

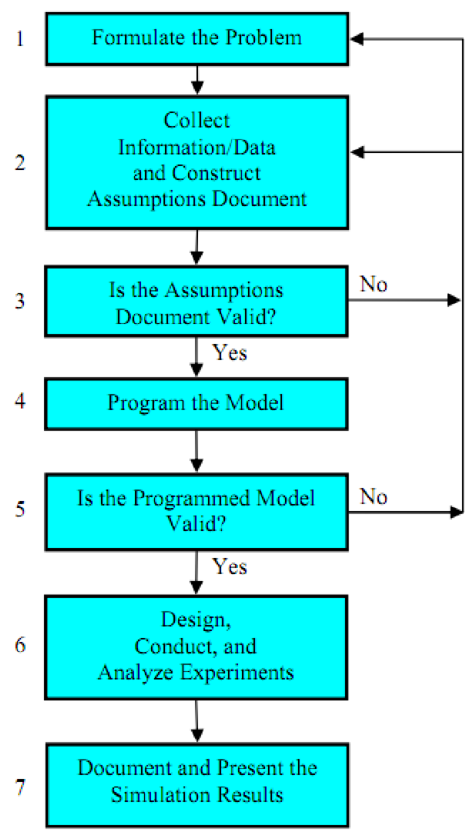

Figure 4. Seven steps for conducting a successful simulation study. Adapted from “How to build valid and credible simulation models,” by Law, A. 2006, *Proceedings of the 2006 Winter Simulation Conference*, p. 26.

Stage 6 involves setting up the experiment with the model and defining run settings such as replications and run length. This could include modifying the model logic and assumptions as necessary to reflect those of a proposed system. Stage 7 involves documenting the assumptions and results of the model. An animation should be added for final presentation. The final presentation should consist of discussion of the results, their validity, and the associated implications. A visual outline of these steps is presented in Figure 4.

DES applications.

DES has been used for a wide variety of purposes, due to its flexibility, easy to learn graphical user interface, and low computing cost. Specific examples of DES studies include a study performed by Gunal and Pidd (2007), which aimed to provide hospital administrators with a model to aid in the formation of hospital policies. The model captured the dynamic nature of the hospital environment by integrating three smaller DES submodels of the emergency, outpatient, and inpatient hospital departments. The inputs included patient arrival volumes, arrival times, hourly staff volumes, etc. Specific waiting times were the variables of interest, as waiting times are important performance variable in the healthcare industry.

DES has also been used to help NASA determine the feasibility of goals for the completion of a segment of the International Space Station (Cates and Mollghasemi, 2005). This model used historical data for mission completions to predict a future mission completion date. The outputs from the DES model matched the pre-planned completion date.

Not only has DES been used to predict performance of specific systems, but it has also been used to develop methods for the evaluation of general systems. For example, Maccubbin (2000) used DES to illustrate the effectiveness of a method designed to evaluate improvements to any type of change-mode parking facility (i.e. parking facilities at airports or rail stations). The method is an 8-step process adapted from current methods of system analysis. Maccubbin's method is tailored to evaluating change-mode parking facilities. The steps include identifying the problem, data collection, and identifying alternative strategies. Using this method, Maccubbin (2000) was able to demonstrate that automated directional signs (out of a variety of intelligent parking solutions), were the best solution for reducing patron travel time in a hypothetical parking facility. The final solution determined by following the steps of the method was supported by the results of a DES simulation.

The previous section described the correct method for conducting a DES simulation study that capitalizes on the advantages of DES and minimizes its limitations. From these studies described, it has been demonstrated that DES has a broad range of problem applications, from policy implementation to project management to system evaluation. The next section will describe DES studies specifically geared toward solving parking system problems.

Parking Simulation Studies Using DES

Lu et al. (2009) performed a simulation study to evaluate the effect that their proposed VANET-based SPARK scheme would affect a parking facility for a large Canadian mall. The variable of interest was the searching time delay. This was measured as the time that elapsed from the time a vehicle entered the parking lot to the instant that a vehicle found a suitable parking space. Vehicles arrived at each of 3 entrances at a rate of 6 vehicles per minute.

Two types of drivers arrived at each entrance: type 1 drivers that searched only for the best parking spaces (i.e. those located at entrances or other attractions) and type 2 drivers that searched for any available space. The drivers drove at a speed uniformly distributed between 9 and 11 km/h (i.e. a random speed between 10 percent below and above the posted speed limit of 10km/h). The probability that an arriving vehicle represented a type 1 driver was p = [.10, .30, .50, .80]. There were four types of simulations, each with a different p value. The probability that an arriving vehicle was a type 2 driver was denoted as $1 – p$. The results of the study show a decrease in the search time delay when the SPARK logic is used versus the real-world logic outlined in the previous paragraph.

Fries et al. (2010) conducted a simulation study to evaluate the effect of real-time parking information on the daily parking activities of a small rural campus. The scaled model was built in VISSIM, a software program for traffic simulations and pedestrian-traffic interactions. The model was calibrated and validated by matching travel times and traffic volumes levels to their actual observed values, with a certain percentage of error. The real-time parking information was disseminated by three variable-message signs set up along a perimeter road. PST decreases of 15% were converted to dollars and significant cost savings were found.

Harris and Dessouky (1997) also conducted a simulation study that analyzed parking availability at a university. Instead of studying the effect of an SPS on a university, they analyzed the ideal amount of parking spaces for each type of patron utilizing the campus parking system. After manipulating the number of spaces allotted to each patron by altering the current layout, the researchers found that an alternative layout existed that reduced the number of balked cars and increased resource utilization.

From the literature review, it is concluded that as society continues to expand, efficient systems for parking management have become a necessity. First, parking challenges in congested and growing environment (i.e. University campuses) were explored. PST emerged as a variable of interest when evaluating parking systems. Methods of disseminating real-time parking information were described, methods of modeling parking search behavior were explored, and a modeling tool, DES, was discussed. Several studies using DES to analyze parking problems have set the precedent of DES being a viable tool for evaluating SPS. This study added to the scarce literature of using DES as a tool for evaluating SPSs on PST in an above-ground university lot without metered parking. It also provided a preliminary resource upon which ERAU can conduct in-depth assessments of how SPSs will affect its unique parking environment.

Method

Problem Statement

The parking system for Embry-Riddle Aeronautical University (ERAU) located in Daytona Beach, FL, was chosen as the system for experimentation in this simulation study. During fall and spring semesters, parking lots on the ERAU campus are noticeably congested, resulting in long searches for available parking spaces. This is especially evident during the work week at mid-day.

ERAU parking lot description.

ERAU's Daytona Beach campus has a total of 21 distinct parking lots that service over 5000 parking patrons consisting of undergraduates, graduates, faculty, and staff Embry-Riddle Aeronautical University, 2011a). The campus lots are divided by patron type (i.e. faculty/staff, commuter students, and student residents). Parking lots are designated for each individual patron type, all three, or a combination of two. In addition to automobile parking, the campus also offers 12 designated motorcycle parking areas. A campus parking map illustrates the total campus parking system in Figure 5. A typical parking lot was selected for this study because it was believed by the author to be a representative sample of the other university parking lots, it had the ideal observation point from which data could be collected, and it had been observed to grow full enough during peak hours to observe the benefits of an SPS.

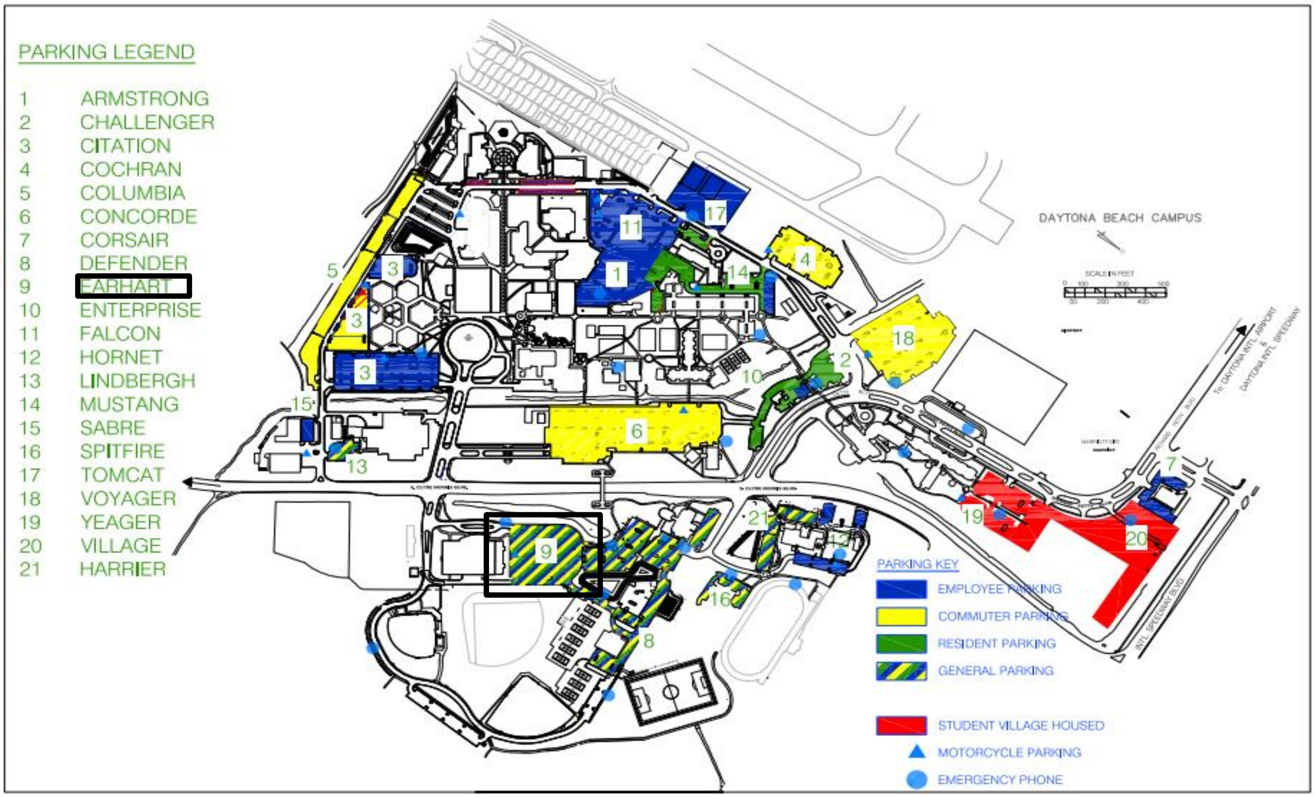

Figure 5. ERAU parking map 2011-2012. Adapted from "Parking," 2011c, *Campus Safety and Security Department*, *Embry-Riddle Aeronautical University*, retrieved from http://www.erau.edu/db/safety/parking-map1.pdf

The parking lot chosen for the study is named Earhart. It is one of 4 lots that are divided from the main campus by a 4-lane, 2-way road named South Clyde Morris Boulevard. The Earhart parking lot services the ICI center, a multipurpose facility over 50,000 square feet that is primarily used for sporting events Embry-Riddle Aeronautical University, 2011b). A satellite photo of the parking lot is shown in Figure 6. The thick white box outlines the portion of the lot under study. A great majority of patrons park in Earhart and cross Clyde Morris to participate in activities on the main campus during midday when the main campus lots are full. It was the only parking lot, at the time of the study, which allowed all patron types to park within its limits. Only a neatly divided portion of Earhart is considered for modeling ease. The portion of the Earhart lot that is under study has 234 regular parking spaces and 7 handicapped parking spaces.

Figure 6. Aerial satellite photo of the portion of the Earhart parking lot under study. Adapted from U.S. Geological Survey. 2011, retrieved from https://maps.google.com

The parking lot was chosen because of its distinctive entry and exit points, along with its well-defined perimeter.

Assumption Documentation

Law (2006) and Kelton et al. (2010) stated that models of systems carry a set of assumptions about workings of the system that should not affect the variable of interest. These assumptions allow experimenters to ignore irrelevant variables to help focus on the main factors of the study and simplify the problem. The following section details the assumptions of the models used for this study.

- The parking lot activity was only simulated over a period of 1.5 hours. The variable of interest, PST, is assumed to be greatest as the parking lot reaches maximum capacity. This was assumed to occur between the morning hours of 10:30am and 12pm.

- The parking spaces are the resources of the parking system. They were categorized into units of about 24 spaces, or half of an aisle. These 11 parking units each had a resource capacity that equals the number of empty spaces in that unit. They were grouped into units for modeling ease. This is based on the Yan-Zhong et al (2006) model. In the simulation, each of the parking spaces has a distance equal to the midpoint of the unit that it belongs to. It is assumed for any parking unit, the time it takes to travel to the furthest spot away from the entrance would be negated by the time it take to travel to the closest spot to the entrance. The stations and their midpoints are shown in Figure 7.

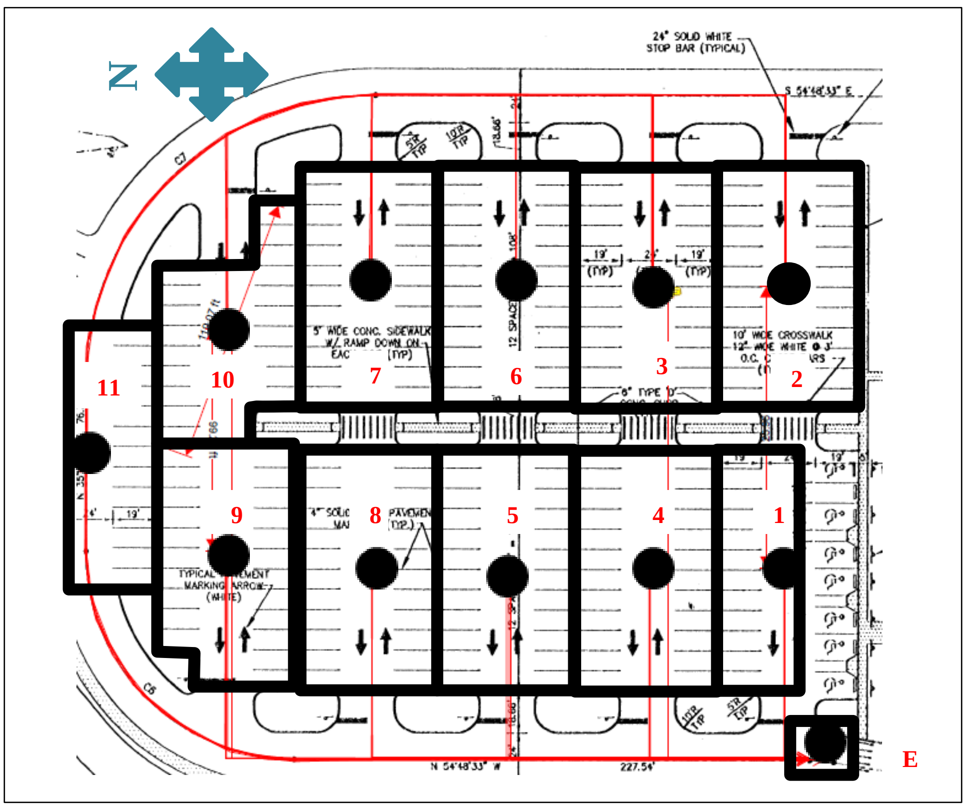

Figure 7. Blueprint with numbered outlines of stations and circles representing station centers. Adapted from "Embry Riddle Aeronautical University: Field House Site," by Z. Cohen & associates, Inc., 1993. p. 3.

- Patrons were not counted individually, but by vehicle (i.e. two patrons arriving in one vehicle are counted as one patron).
- The scope of the model only included the main part of the Earhart parking structure, consisting of 234 parking spaces.
- Due to the geographical properties of the lot, the most desirable parking spaces were those located closest to the main entrances. Every other parking space decreased in desirability as its distance increased from the parking entrance.
- The PSTs of patrons entering from the three other entrances of the parking lot were similar to the search times of patrons entering from the main entrance.
- The implementation of a SPS did not impact the arrival rates, parking durations, and driving speeds of patrons or the geographic properties of the parking lot.
- Once patrons parked, they stayed for the duration of simulation. Departures from the lot by previously parked cars were simulated by adding capacity to each of the parking stations.
- Under the SPS logic, all patrons proceeded to available desirable parking via the most direct route.
- Under the SPS logic, patrons only enter a lot if there is an available spot.

Model Development

Model descriptions.

The first part of the experimental design included defining the descriptions of the systems under comparison. The models described in the following sections are abstractions of how the systems operated. For clarification, the Arena model that was built to represent the Earhart parking lot is called the base model. The Arena model that operates under an SPS is referred to as the experimental model.

Existing Earhart parking system (base model).

Patrons arrived at the parking lot at different rates based on the time of day (i.e. half-hourly). Once a patron entered the parking lot, the parking search began. The PST was terminated once a patron begins parking in a spot.

Patrons utilized a search behavior based on probabilities in order to find a parking space. Once a patron came upon an available space, they began to park there. The patron remained parked for the duration of the simulation. Since the PST was the variable of interest, the exact parking durations and departures of specific cars was not modeled with detail. Departures were modeled as events that add capacity to the each station and the lot as a whole. In theory, a departure is another parking space addition and another opportunity to observe PSTs.

Proposed smart parking system (experimental model).

The model description for the proposed SPS is discussed in this section. It is important to note that each SPS has its own method of disseminating parking information. Most systems use sensors to detect parking space occupancy, but some use variable message signs, and others use individual units in each car to display availability. The SPS model does not reflect that level of detail, but it is representative of the process of information dissemination. Patrons entered the parking lot at their normal arrival rates. The times of arrivals were recorded and used to calculate PST (i.e. used as a starting point for PST). It was assumed that patrons only enter a lot if it has an available spot and the probability that the spot will still be available once they enter the lot was high. Patrons, once in the lot, were shown the nearest available parking space. This dissemination occurred instantly or near instantly. The closest available parking station with free spaces was designated for the patron. Patrons, following the search behavior of minimizing walking disutility, chose to park in this spot. The capacity of the station decreased as soon as a space was designated for a patron. This minimized the chances of two patrons trying to park in the same spot.

As with the base model, departures were modeled as capacity adding events. Patrons that found parking remained parked for the duration of the simulation, but departures were modeled as additions to capacity so that more patrons could park.

Data Collection

The data needed for construction of the computer simulated model of the parking facility was collected on site at the Earhart parking lot. Data was collected through observation by the author and one video camera on the second story of a nearby building. Arrival rates of patrons, preferred parking search strategy, number of cars parked in each area of the parking lot at the beginning of the simulation time, automobile traveling speeds within the lot, departure rates, parking stations that patrons depart from, and the geometric properties of the lot (i.e. distance between groups of parking spaces), were collected. The data used for the models was collected on 4 days (i.e. Monday –Thursday) from 10:30am – 12:00pm. All of the model inputs and their units are listed in Table 1. The data collection sheet can be found in Appendix A. The observed PSTs for the Earhart lot and the recorded distances between stations can be found in Appendices B and C, respectively.

Table 1
Data Collection for Modeling and Validation

Input Name	Measuring Units
Number of Cars in Each Station at Start	Cars
Arrival Rates at Entrance	Number of Cars per 30 minutes
Driving Speed	Feet per second
Number of Spaces	Spaces
Distance between Parking Stations and Entrance	Feet
Departure Rates from Each Station	Cars per 30 minutes
Parking Search Times for Validation	Seconds

The distribution of the driving speeds was analyzed using a goodness-of-fit test from an add-in of Arena called Input Analyzer. This provided the driving speed parameters for use in the model. Input Analyzer is a data analysis tool for conducting goodness of fit tests. Goodness-of-fit tests allow for the testing of the null hypothesis of the data points fitting a particular distribution. The null hypothesis is as follows:

"H_0: The X_i's are random variables with distribution function $\hat{F}$"

Where $\hat{F}$ is the distribution function (Law & Kelton, 2003). Input Analyzer gives a *p* value for each test it performs on the data for each distribution. Distributions with *p* values of more than or equal to .10 are acceptable distributions for modeling of data. If no theoretical distribution ($p < .05$) can be found, an empirical distribution formula is used for Arena.

Chi-square tests are type of goodness-of-fit test that can be used to test the null hypothesis of whether collected data belong to a distribution with function $\hat{F}$. First, the collected data must be divided into k adjacent intervals. N_j is computed as the number of observed data points that fall within each interval j. Next, p_j is computed as the number of expected data points that would fall in each interval if the sample came from the theoretical distribution being tested. Equation (5) outlines the formula for calculating the p_j of discrete data.

$$p_j = \sum_{a_{j-1} \leq x_i < a_j} \hat{p}(x_i) \tag{5}$$

where p̂ is the mass function of the theoretical distribution. The test statistic formula is found in Equation (6).

$$\chi^2 = \sum_{j=1}^{k} \frac{(N_j - np_j)^2}{np_j} \tag{6}$$

The smaller that χ^2 is, the better the fit of the distribution because χ^2 is a measure of the difference between the observed and the expected data points falling within each interval (Law & Kelton, 2003).

Arena

Arena 13.9 was the version of Arena used for this study. Arena is a simulation software package produced by Rockwell Automation, Inc. Arena is designed to give organizations the ability to simulate systems with the intent of making system modifications in order to optimize performance. Arena is based on the SIMAN modeling language but primarily uses a graphical user interface to create logical models reflective of system characteristics. Arena offers varied levels of modeling detail through packaged modules for modeling common system functions.

Modeling techniques.

In this section, important aspects of the models are described. This section offers insight into how certain characteristics of the Earhart parking lot were modeled in Arena.

The assign module was used to assign a driving speed to each patron once they entered the simulation. This was chosen from a probability distribution that described the driving speed sample. In the base model, after proceeding to the first station (i.e. the entrance), patrons were routed to other stations via decision modules that contained programmed probabilities of patrons searching a particular station. These probabilities were gathered from a sample of observed events during the data collection period. When a patron went through an entire probability route without finding parking, the patron left the lot.

In both the base and experimental models, patrons checked each station via a decision module to determine whether or not a variable, representing the capacity of that station, was full or not. At the beginning of each simulation, the capacity for each station was set to the average available spots observed over the 4 simulation days at exactly 10:30am. In the base model, if a station was full, a patron moved to another station via a route. This route was determined by the next probable location that a patron would search based on observed events. This is shown in Figure 8. In the experimental model, if a station was full, the system checked the next closest station to the entrance without actually moving the patron. If the station had unused capacity, the time that it took the patron to reach that station was recorded and the patron was placed in an infinite hold. The experimental search logic is shown in Figure 9.

Base Model Flow Chart

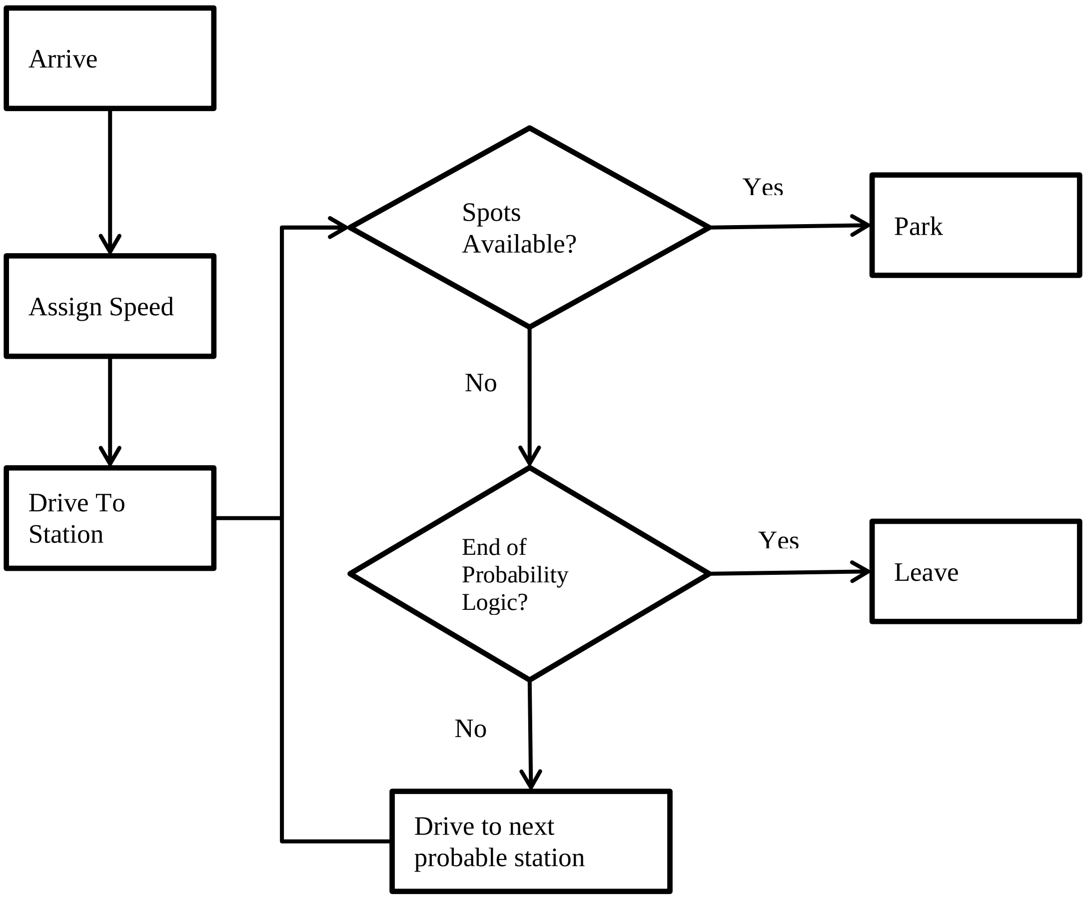

Figure 8. A flowchart showing the parking search process for the base model.

Experimental Model Flow Chart

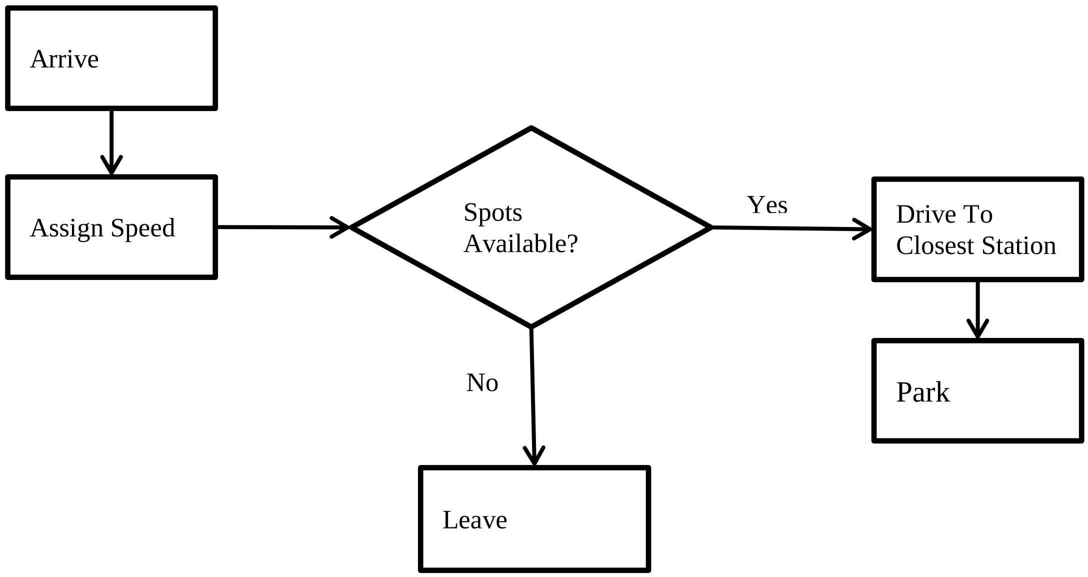

Figure 9. A flowchart showing the parking search process for the experimental model.

An important aspect of Arena, as related to the goal of this study, is the ability to model the movement of entities through systems. The movement of patrons through the parking lots was modeled using the advanced transfer functions (e.g. routes and stations) within Arena. The distances of the routes reflect the actual distances of between entrances/exits and grouped parking spaces (i.e. stations) within the Earhart parking lot. The time it takes to complete each route is its distance divided by the patrons driving speed.

Departures, as previously mentioned, were modeled as capacity adding events. Once a departure entity was created, it was sent through a decide module that had a probability assigned for each station. The probability of a departure from different areas of the parking lot was determined from the data. Once it left the decide module, it was sent through an assign module to increase the capacity variable for the particular station by 1. Finally, the departure entity was disposed.

Independent variables.

The IVs and DVSs are listed in Table 2 at the end of the Dependent Variable section. The parking search strategy (PSS) was the independent variable in this study and was reflected through the author's manipulations of the model logic. In the base model logic, a patron would follow one of multiple routes that allowed the patron to survey the parking lot to search for a space. The routes had up to four turns and the probability of a patron making a turn was based on the proportion of patrons that were observed making that turn in real life.

In the experimental model logic, the patrons followed the shortest route to an assigned parking spot. The SPS assigned available parking spots that are closest to the entrance. It was assumed that patrons would park in the most desirable space. Since patrons do not enter the lot if it is full, no patrons circle and wait at any time. For simulation purposes, patrons arrived at the full lot but leave immediately if all the spots are filled.

Dependent variable.

The dependent variable was PST. PST was defined as the time that elapsed between the arrival of a patron and the seizure of a parking space resource. The arrival time was assigned by the assign module to each entity as they entered the system. The entity then traveled through the appropriate routing logic. After an entity seized a parking space, the elapsed time between the arrival time and the seizure was recorded through the record module. It was hypothesized that the PST of the SPS experimental model would be significantly lower that the PST of the existing base model.

Table 2
Independent and Dependent Variables

Variable Type	Variable Name	Levels or Units
Independent	Parking Search Strategy (PSS)	Observed Parking Strategy vs. Smart Parking Search Strategy
Dependent	Parking Search Time (PST)	Seconds

Verification and Validation

Kelton et al. (2010) and Law (2006) provided outlines for verification and validation of simulation models. Kelton et al. (2010) defined verification as ensuring the model operates as the research intends it to. For example, if the researcher would like one type of entity to follow a specific logical path apart from other entities, then verification ensures that the entity actually follows the set path. Validation is the process of ensuring that the model operates as the real system does in real life. In the above example, if the special type of entity does not actually follow the separate logical path in real life, then the model would not be valid.

There are many ways to verify a model and no one way is accepted by all. It is best to use a combination of methods in order to ensure that the model operates as intended, as was the case with this study. The first method of verification for this study involved altering the arrival rate so that it was possible to follow exactly one entity of each type through the entire system. This is recommended by Kelton et al. (2010) so that the researcher may have a better look at the inner workings of the system. The second method involved the models being run for extended periods of time with the objective of finding unusual model behavior. After this behavior was addressed, the final verification test involved presenting the models in front of a group of knowledgeable individuals. The models were open for critique and verification.

For the validation stage, the base model was used. A representative sample of driving speeds was taken, and a probability distribution that described the sample was programmed in the model. To validate the search strategies, driving speeds, and the model itself, the PSTs for modeled patrons to find parking were compared to PSTs taken during the data collection period.

The two samples of PST were compared using a *t*-test for two independent samples to verify that they were not statistically different.

In summary, the methods section involved defining the problem and limiting scope of this study to the Earhart parking lot. The assumptions of both models were defined, with the most notable assumption being that parking spaces were grouped into stations by proximity. The models were then described generally and the data needed to build the models was specified. Then, the Arena software and specific modeling techniques were described, as well as the independent and dependent variables. Finally, the verification and validation procedures were outlined.

Results

In this section, the main parts of the final Arena models are depicted, the model inputs (i.e. arrival rates, driving speeds, etc.) are described, and the results of the statistical tests (i.e. validation, and independent samples *t*-tests) are provided.

Modeling Results

The following figures show the main parts of both the base and the experimental logic. Figure 10 shows patrons entering the base model simulation, being assigned a driving speed, and proceeding from the entrance to one of 5 parking stations. Figure 11 then shows the logic for a patron searching down a particular aisle. The full base model can be found in Appendix D.

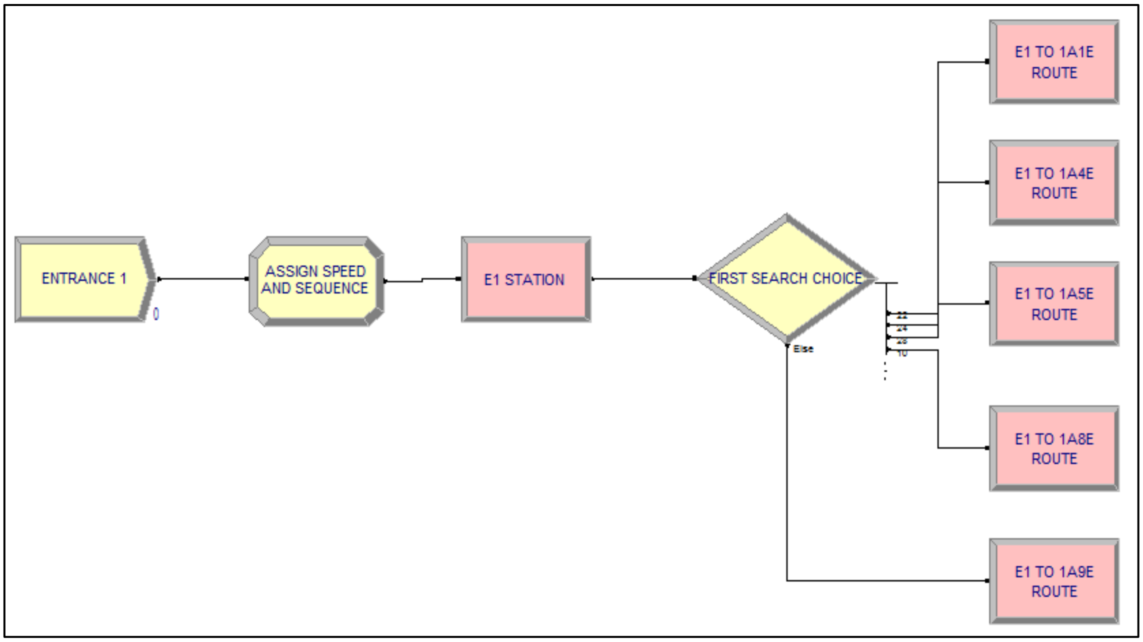

Figure 10. Base model arrival and first station search choice logic.

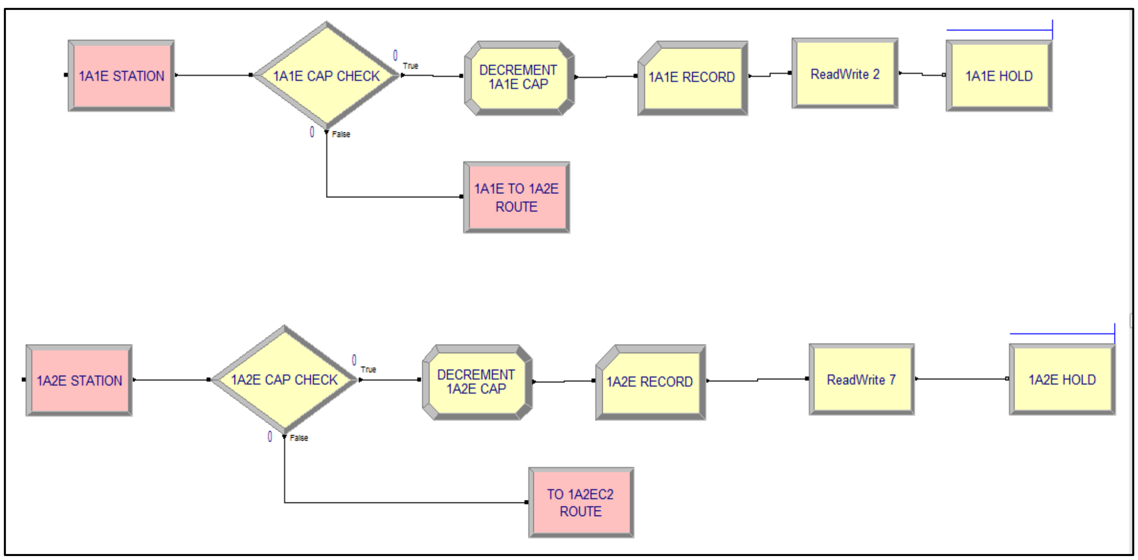

Figure 11. Base model aisle search logic.

Figure 12, in contrast, shows the PSS for the experimental model. In this logic, a patron arrives, is assigned a driving speed, and then checks each station by distance for available spots before moving to an open space. The full experimental model can be found in Appendix E.

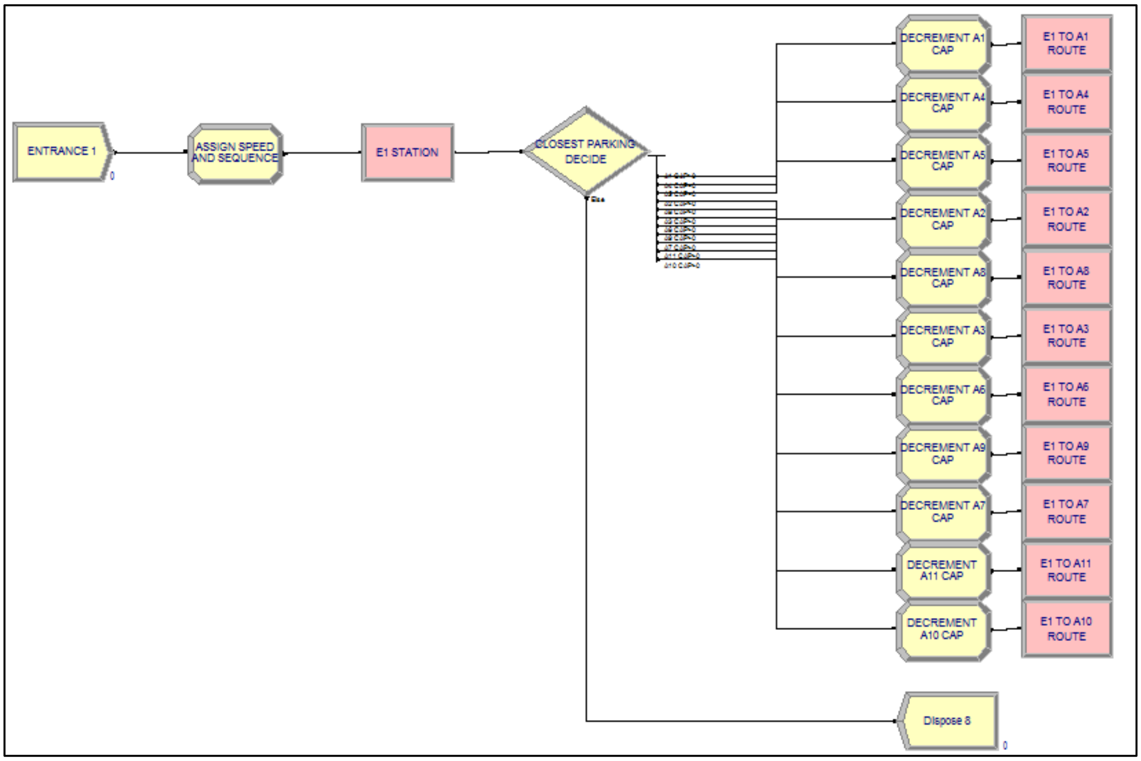

Figure 12. Experimental model arrival and station search choice logic.

The departure logic contained within both models is shown in Figure 13. This shows the departures being modeled as a signal to add capacity to the stations depending on the observed departure rates from each station.

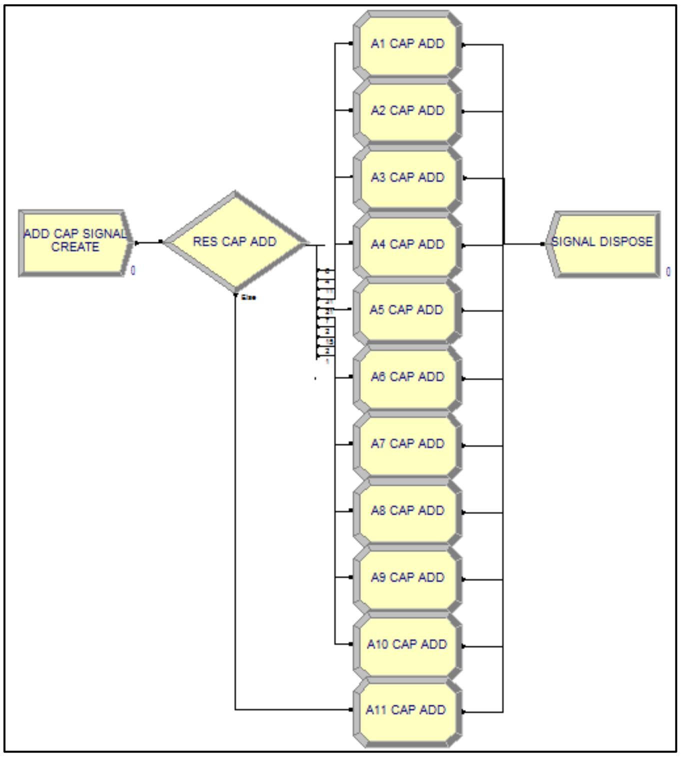

Figure 13. Base and Experimental model departure logic.

Data Analysis Results

Arrival rates.

The arrival rates for each day were entered into Arena with a schedule. The schedule is displayed graphically in Figure 14. The arrival schedule was the same for both the base and experimental models. The arrivals were put into a schedule because, based on the observed fluctuations in arrival rate, it was determined that a non-stationary arrival rate would be appropriate for modeling the arrivals.

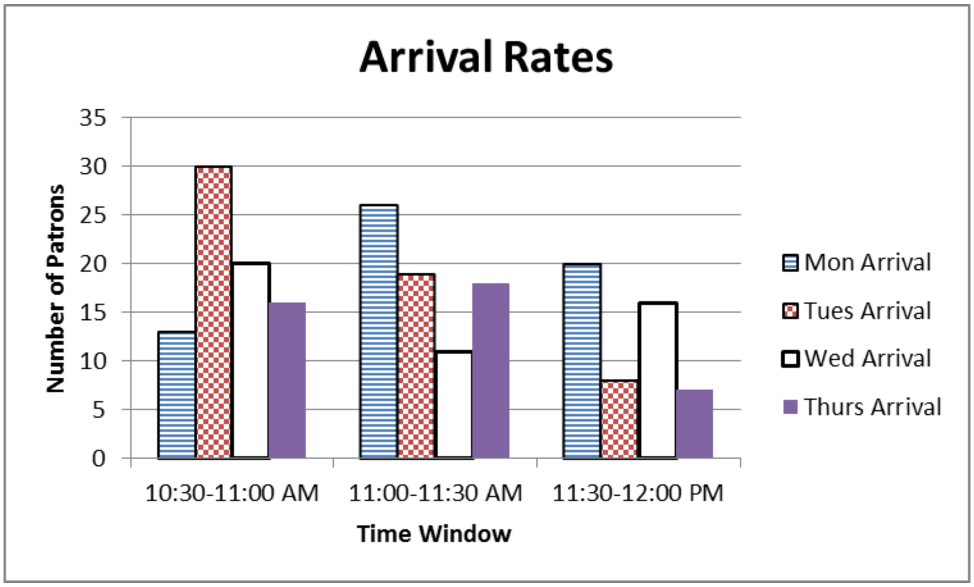

Figure 14. The arrival rates for each time window by day.

Departure rates and probability from each station.

The number of departures was also entered into Arena with a schedule. As with the arrival rates, departure rates were by the half hour. The departure rate schedule was the same for both the base and experimental models. Again, a schedule was used due to the observed non-stationary departure rate. The departure rate is displayed graphically in Figure 15. The station from which each departure occurred was also recorded. These observed events were used to determine which station a departure occurs from when a departure occurs on the schedule. These probabilities are shown in Figure 16.

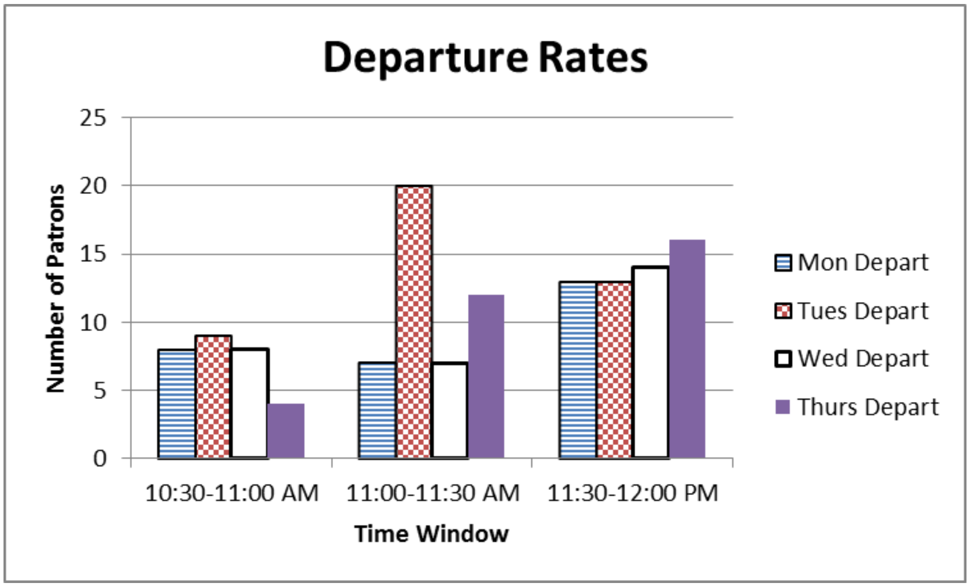

Figure 15. The departure rates for each time window by day.

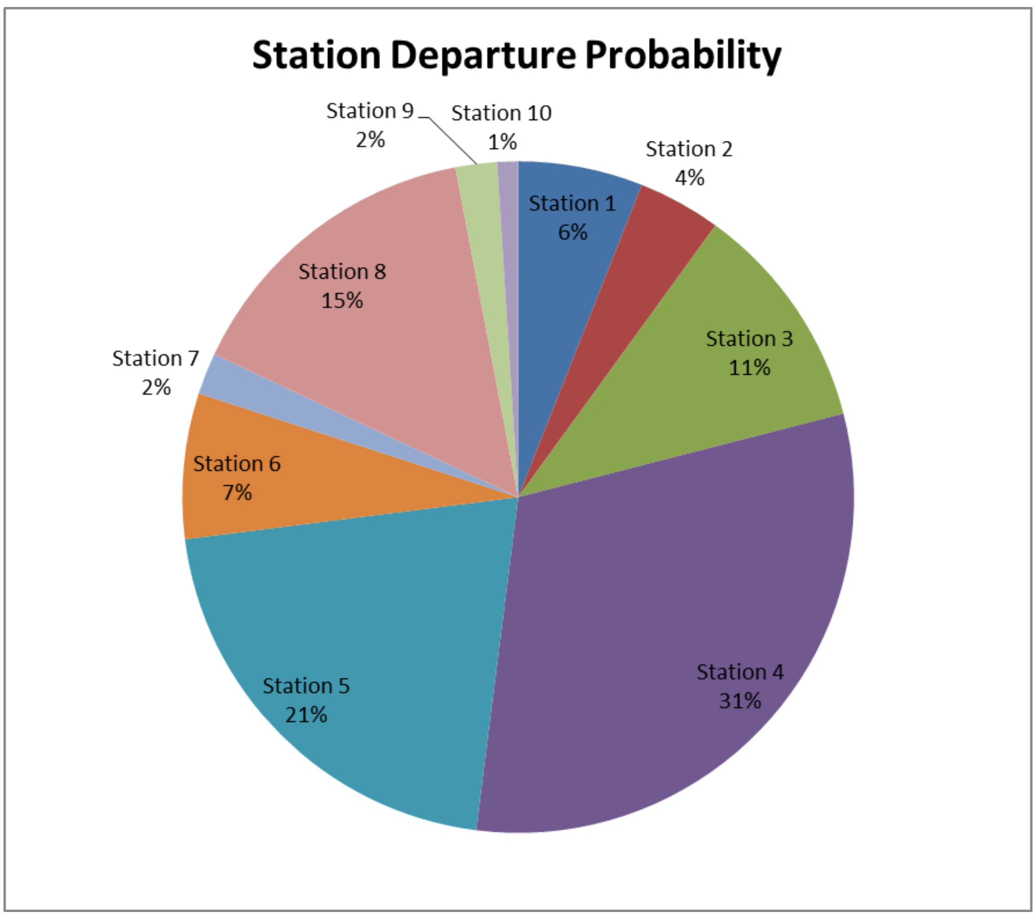

Figure 16. The probability of a departure originating from a station.

Base model search probabilities.

The search logic for the base model was based on the observed PSS displayed by parking patrons. The percentages of patrons entering the lot and searching down each aisle (i.e. two stations) can be found in Figure 17. These percentages were treated as search probabilities in the base model logic. The rest of the search probabilities, categorized by search choice number and last searched station, can be found in Table 3.

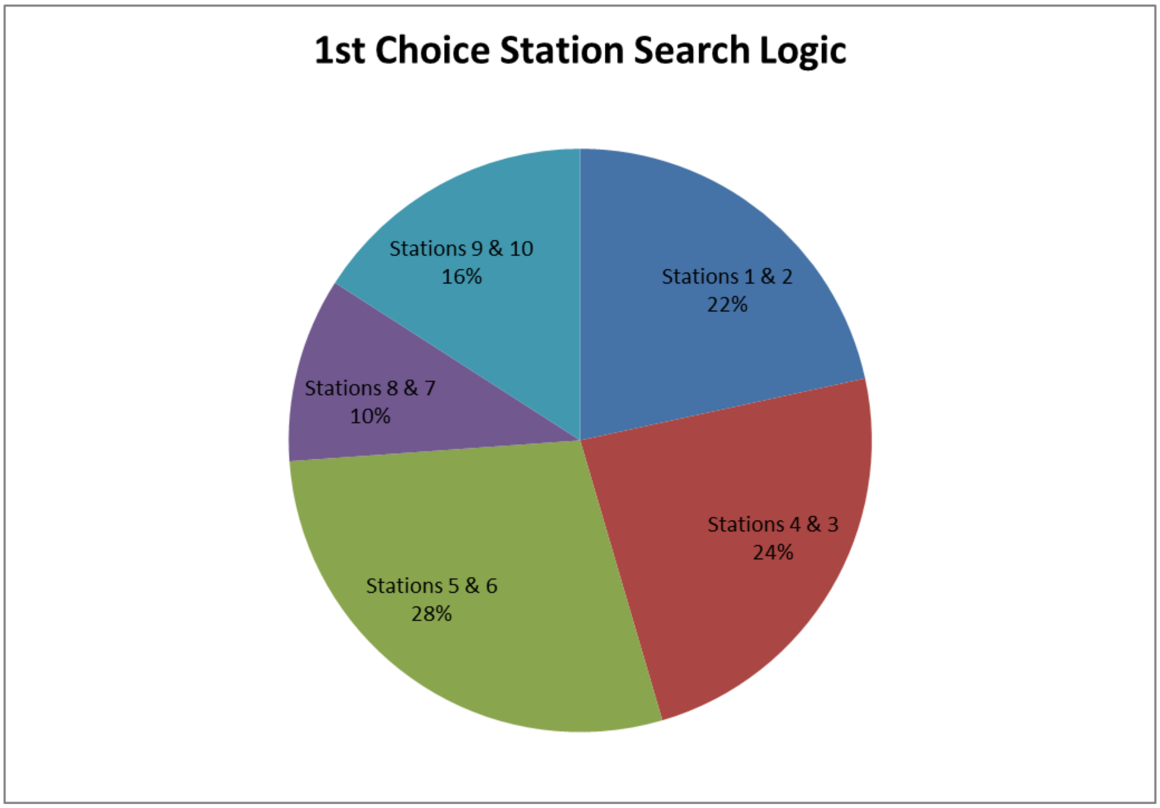

Figure 17. The probability of searching a pair of stations when arriving from the entrance.

Table 3

Observed Search Probabilities for the Earhart Lot

Search Choice	Departing Station	Arriving Station	Observed Percentage
2nd	Station 2	Station 3	0.58
		Station 6	0.33
		Station 7	0.08
	Station 3	Station 6	0.57
		Station 7	0.21
		Station 10	0.21
	Station 6	Station 3	0.27
		Station 7	0.55
		Station 10	0.18
	Station 7	Station 3	0.5
		Station 10	0.5
	Station 10	Station 6	1
3rd	Station 4	Station 1	0.33
		Station 5	0.67
	Station 5	Station 8	0.8
		Station 11	0.2
	Station 8	Station 9	1
	Station 9	Station 11	1
4th	Station 6	Station 3	1
	Station 7	Station 6	1

Model capacity at initialization.

The number of spots available in each station was recorded over the 4-day data collection period. These numbers were averaged over the 4-days for each station and then rounded up to the nearest whole integer. This average was used as the beginning capacity for each simulation start. The data can be found in Table 4.

Table 4

Resource Capacity at 10:30am

Station	Day *Monday*	*Tuesday*	*Wednesday*	*Thursday*	Integer Avg
1	0	0	0	0	0
2	0	0	0	0	0
3	1	0	0	0	1
4	0	0	1	0	1
5	1	0	0	1	1
6	5	2	0	9	4
7	17	11	3	18	13
8	1	0	0	2	1
9	1	1	0	12	4
10	14	16	7	17	14
11	11	9	4	12	9

Driving speed distribution results.

Input Analyzer, as previously mentioned in the Data Collection section, was used to determine if the data collected on driving speeds could be described with a particular probability distribution. The descriptive statistics for the driving speeds can be found in Table 5. The units for the table are feet per second. Based on a Chi Square Test for best fit, the researchers chose a triangular distribution (p = 0.264) to describe the driving speeds within the parking lot. The probability distribution chosen for this data can be found in Equation (6). A histogram of driving speeds can be found in Figure 18.

Table 5

Descriptive Statistics for Driving Speeds Sample

	n	*M*	*SD*
Driving Speeds	100	16.4	3.79

$$TRIA\ (8, 14.2, 27) \tag{6}$$

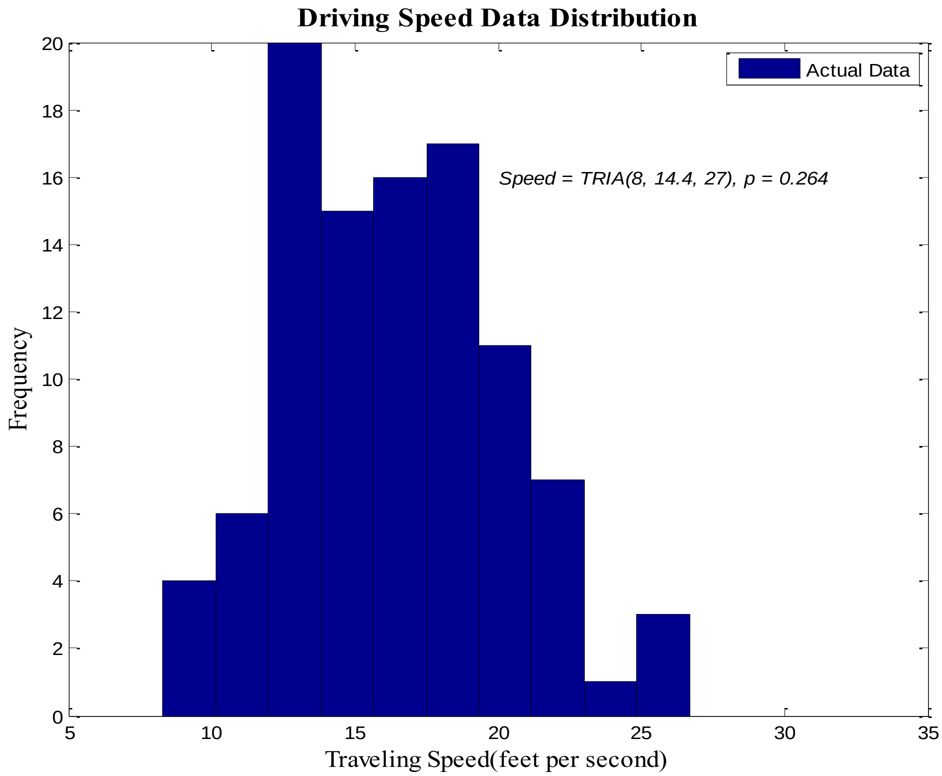

Figure 18: Driving speed data distribution.

Verification and Validation Results

As previously mentioned, the base and experimental models were verified in 3 ways. First, the arrival rate was modified so that only one patron arrived during the simulation. This patron was followed through the model step by step while model variables and overall model behaviors were monitored for logical accuracy. Second, both models were run with extremely large arrival rates and checked for logical results. The result was that both models showed large amounts of patrons departing the parking lot without having found parking. Finally, the models were open to verification and critique from a group of knowledgeable individuals at a thesis defense.

Before the construction of the experimental model, the base model was validated by comparing its PSTs with those of the Earhart parking lot for 4 days between 10:30am and

12:00pm. The descriptive statistics for these two samples are found in Table 6. The PSTs for the Earhart lot and Base model are plotted in Figure 19.

Table 6

Descriptive Statistics for PST Validation Samples

	Source of PST	*n*	*M*	*SD*	95% CI
PST (seconds)	Earhart Parking Lot	84	24.38	15.77	[22.02, 32.06]
	Base Arena Model	89	27.04	17.57	[24.68, 34.27]

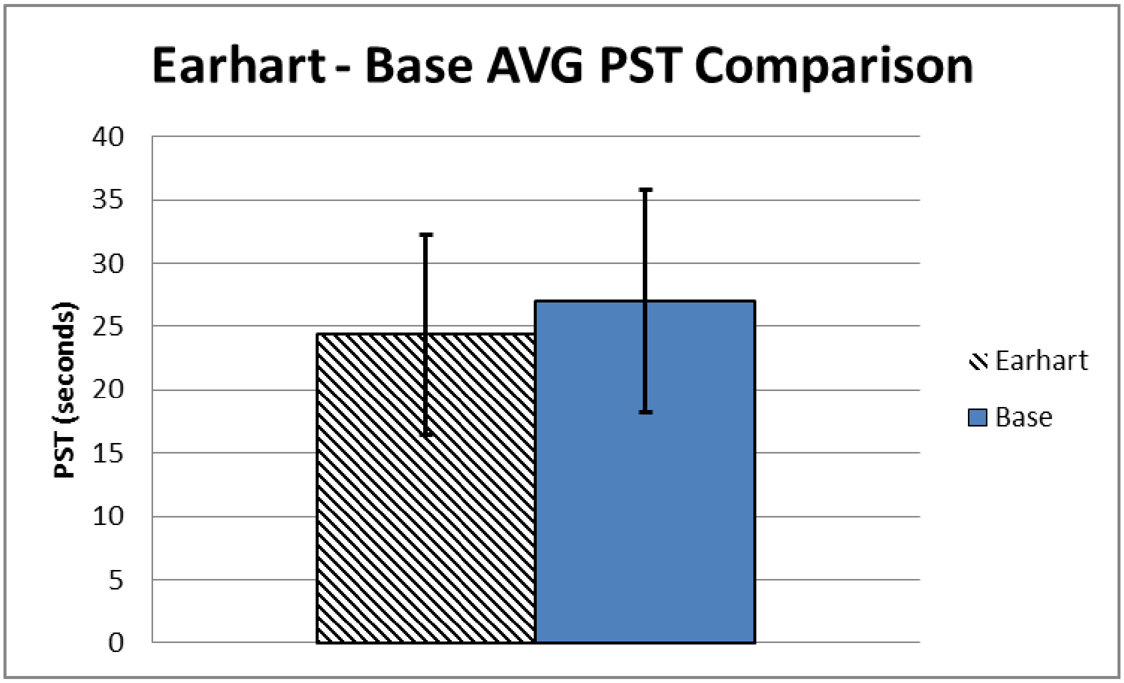

Figure 19. PST for the Earhart lot and base model.

An independent samples *t*-test showed that there was no significant difference between the means of the two samples (t = 1.048, p = .298). These results suggest that the base model is a valid representation of the Earhart parking lot in terms of PST.

Experimental Comparison Results

Once the experimental model was developed and verified, its 10 day PST mean was compared with the 10 day PST mean of the base model. The descriptive statistics for these two samples can be found in Table 7. The samples were recorded from a simulation that was run for 10 simulation days at 1.5 hours a day. The PST is also displayed graphically in Figure 20.

Table 7

Descriptive Statistics for Base and Experimental Model PSTs

	Source of PST	*n*	*M*	*SD*	95% CI
PST (seconds)	Base Arena Model	560	31.29	19.70	[21.92, 44.08]
	Experimental Model	633	20.21	9.06	[10.84, 33.00]

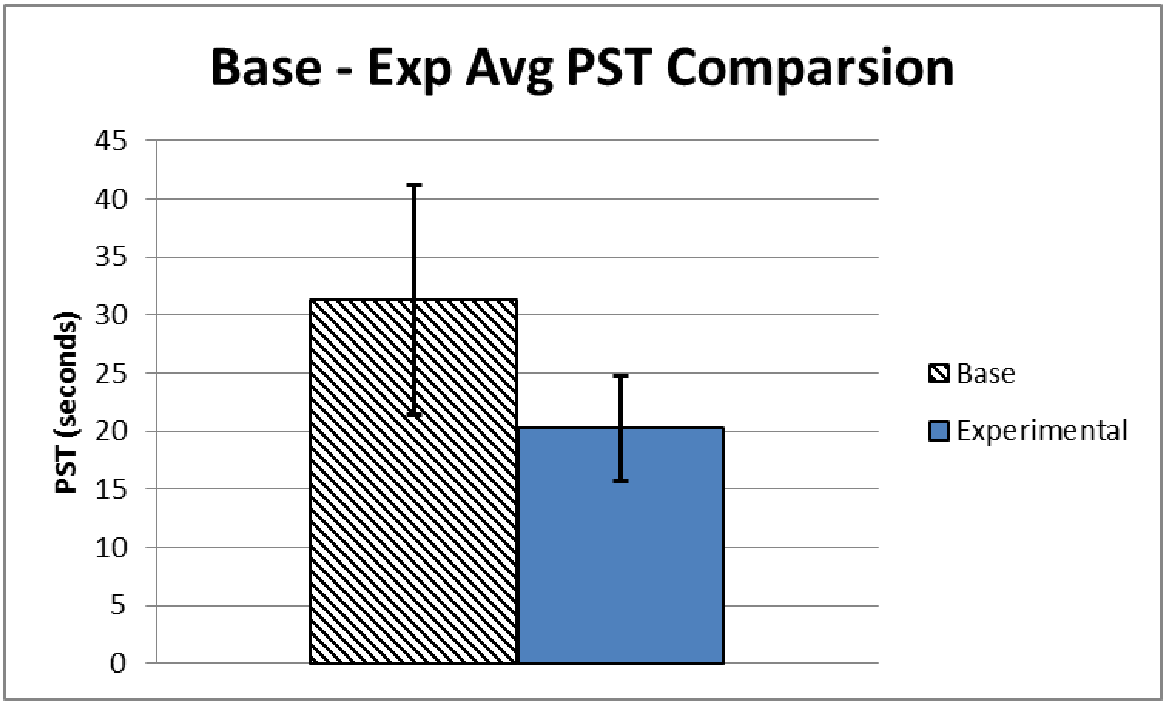

Figure 20. PST for the base and experimental models.

An independent samples *t*-test showed that patrons within the experimental model have significantly lower PSTs than patrons of the base arena model (t = 12.709, p < .001). In summary, a DES base model of the Earhart parking lot was built from the campus lot data. The PSTs from the DES base model (run over 4 days) were found to be statistically indifferent from the PSTs observed in the Earhart lot. Then the logic was altered to make the experimental model reflecting the operation of an SPS. This caused a significant decrease in PSTs by an average of 11 seconds over a 10 day span.

Discussion

The major findings of this study were that the base model is an accurate predictor of PST for the Earhart parking lot, and the experimental model, operating under smart parking logic, produced significantly shorter PSTs than the base model.

Discussion of Results

The significant difference between the base and experimental models is attributable to the manipulation of the independent variable, the PSS. The base PSS is based on observed movements in the Earhart parking lot without a smart parking system. As stated in the literature review, these movements are likely based on factors such as past experience, time of day, and walking disutility. This base model is similar to the probability-based model put forth by Caicedo, Robuste, and Lopez-Pita (2006). The experimental model PSS, however, is based on systematically checking the available capacity of parking spaces from shortest to longest distance from the entrance. The instantaneous dispersion of this knowledge is likely the key factor in reducing the PSTs of drivers in the experimental model. With an SPS, patrons instantaneously know the location of the nearest parking space, even when it is not directly visible. Because no time is wasted investigating stations that cannot be seen from the entrance, patrons experience a lower PST with an SPS. Although no surveys were taken during this study, these findings support the conclusions drawn from Caicedo, Robuste, and Lopez-Pita’s (2006) study. The conclusion from the Caicedo, Robuste, and Lopez-Pita (2006) study was that SPSs reduced PSTs in a below-ground structure.

Economic Impact

The analysis of the means suggests that patrons using a SPS would save an average of 11 seconds in PST per vehicle over a two week period. These are savings that add up over time in fossil fuel usage reduction and lower motor vehicle emissions. However, to help determine whether an SPS should be adopted on the Embry-Riddle Daytona Beach campus, the costs should first be explored.

The costs for an SPS to govern the Earhart parking lot can be estimated from an informal costing method proposed by the authors of a field study analyzing the costs of an SPS for Bay Area Rapid Transit (BART) and the California Department of Transportation (U.S. Department of Transportation 2008). The SPS for the Rockridge BART station consisted of two variable messaging signs along the access highway, as well as six in-ground sensors and 3 base units. The Rockridge BART SPS is similar to the SPS logic used in the experimental model except for the added capability of patrons to reserve parking spaces in Rockridge before they make their trip to the lot.

The California Partners for Advanced Transit and Highways (PATH) researchers estimate that a parking system of that nature would have a capital cost ranging from $150 to $250 per space while the annual maintenance and operations cost range from $50 to $60 per space. The capital cost estimate includes the cost for the sensors, the variable message signs, a voice recognition system, and customized parking software. The operation and maintenance costs include website maintenance costs, customer support, personnel costs, and communication service provider costs (U.S. Department of Transportation, 2007). Using the lowest estimates, an SPS of this type for the Earhart Parking lot would have a capital cost of $35,100 and $11,700 in yearly operations and maintenance costs, respectively.

One possibility to fund the system would be to increase the costs for parking passes for faculty, staff, and students. It is assumed that patrons would only agree to pay for the system if all of the savings, both quantitative and qualitative, were greater than the increase in parking fees. While the current PST savings do not seem to justify such an expensive system, it is likely that an economy of scale could be taken advantage of as more patrons share the cost of a university-wide system and receive greater benefits.

Study Limitations and Further Research

Many of the limitations in this study stem from the assumptions of the models. The first limitation is that the base Arena model has only one entrance whereas the Earhart parking lot has four. The reason for this is because there were too few arrivals at three of the entrances to construct accurate search probability logic. There was a clear main entrance that most drivers preferred to use. In the event that the PSTs of the small amount of drivers from entrances 2, 3, and 4 are not statistically indifferent from the PSTs of drivers from entrance 1, the savings in PST predicted by the models may not be accurate. It is important to note that due to the location of the center of the campus, the parking area preferences programmed into the SPS would be suitable for drivers arriving from any entrance.

Another limitation dealt with data collection. Due to restrictions in camera resources and vantage points, the researcher was not able to videotape the entire Earhart parking lot at once. For example, the 12 spaces on the south east corner of the lot were not visible to the researcher during the data collection. The researcher moved the camera to capture events of interest but may have missed events that would make the model data more accurate (e.g. a departure from a parking space).

The third limitation arises from the grouping of parking spaces into stations by proximity. This could potentially have an impact on the results of this study if it cannot be assumed that the time it takes to reach opposite ends of the stations would offset each other.

The fourth limitation of the study is that the results of this study may not accurately be generalized to estimate the impact of an SPS that would govern the whole ERAU campus. The reason for this is that there are other lots that are very high in demand and operate at 100% utilization for longer periods of time. It loses its desirability because it is one of the furthest lots from the heart of campus. The main reason why it was selected for this study is that the lot had a nearby two-story building that was ideal for lot observation, in addition to being sufficiently large to show the benefits of an SPS. The greatest benefit of an SPS is the saved PST that accompanies advanced knowledge of a full lot. Utilization of the Earhart lot sometimes neared 100 percent during the observation period, but the author suspects that other lots closer to campus may be more heavily used, and thus would show greater benefits from an SPS.

Conclusions

The objective of this study was to investigate how SPSs impact PST using DES. The results of this study further confirm that an SPS can make a positive difference in how people utilize parking lots by reducing PST. As mentioned in the introduction, as our society develops and grows in size, there will be a need to update our old transportation infrastructure to accommodate this new growth. New SPS technology is a promising management tool to improve the parking search process as lots grow larger. The university setting provided a suitable setting to study the effects of an SPS on a small scale (i.e. one parking lot).

DES was a suitable tool for conducting this study because it allows researchers to isolate and experiment with almost any system variable. The parking lot is a fairly simple queuing system to model and DES has been used in the past to investigate SPS effects. The novelty in this study is that DES has yet to be used to evaluate PST in above ground university lots that are on a stickered system. This study also provides a basis for Embry-Riddle to make decisions on the implementation of an SPS in its campus improvements. While there were significant findings for the study and savings incurred by the system, the costs of the system seem to outweigh the benefits (i.e. gas, time, and emission savings). There is reason to believe, however, that the benefits of an SPS would be magnified on a greater scale in which there were many lots to choose from, much like the studies conducted by Thompson and Richardson (1998) and Fries et al (2010). In conclusion, the next step in determining whether or not an SPS would be beneficial to the Embry-Riddle campus is to model multiple parking lots to get a more accurate depiction of PST savings and their economic impact.

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Appendix A. Data Collection Sheet

Time	Arrival				Departure			
	E1	E2	E3	E4	E1	E2	E3	E4
10:30 – 11:00								
11:00 – 11:30								
11:30 – 12:00								

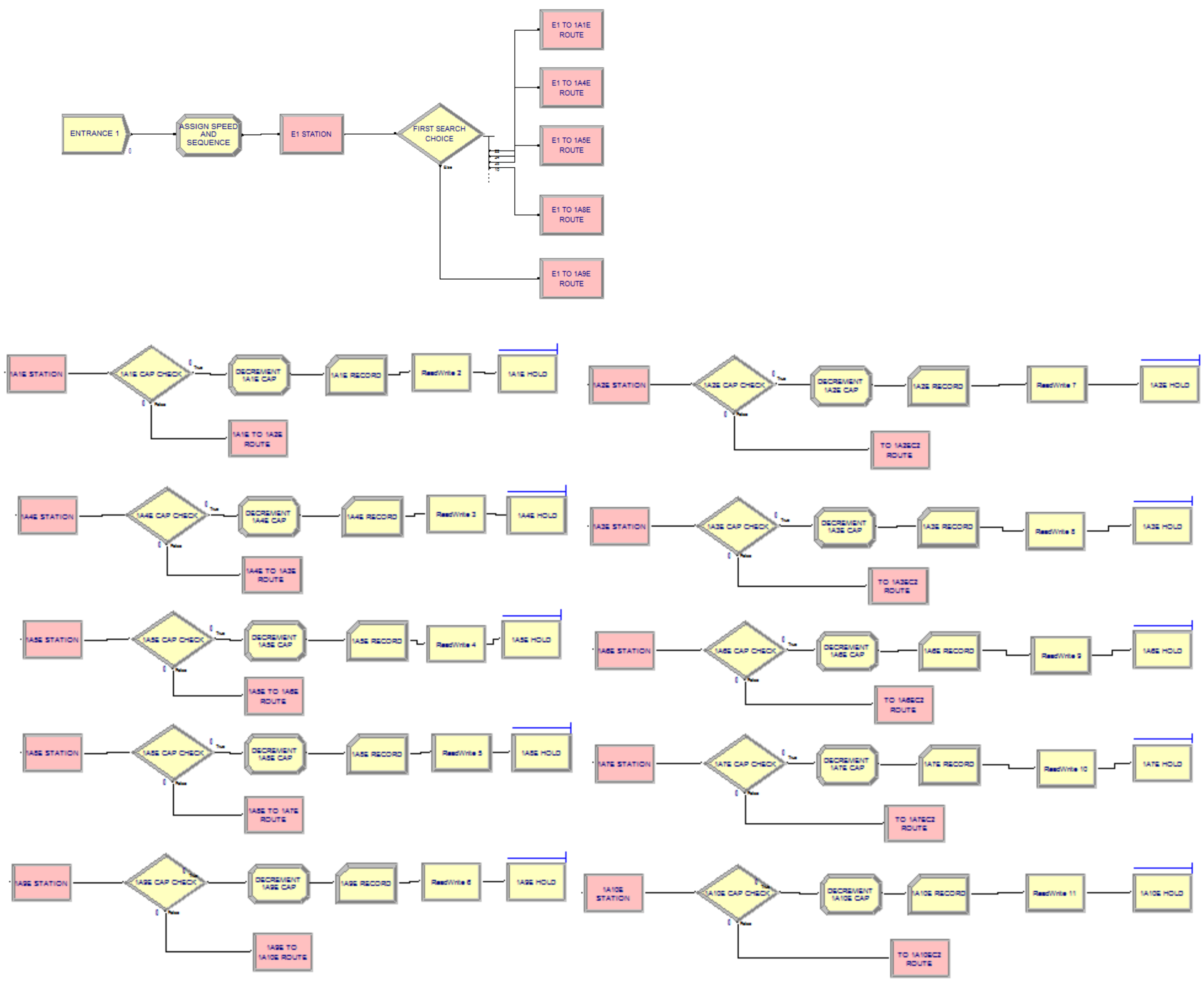
Appendix B. Observed PST from Earhart Lot (seconds)

20.6	21.1	11.6
11.1	16.5	19.6
11.7	13.7	17.4
17.4	35.8	8.6
15.2	37.2	44.3
18.6	25.1	14.5
15.6	75.3	
18.6	28.1	
19	53.4	
16.3	3.9	
18.3	8.3	
5.5	5.1	
17.4	25.7	
5.7	34.7	
27.6	7.9	
26.4	24.5	
6.6	19.6	
3	49.3	
22.4	14.9	
5.7	30	
3.6	69.8	
23.5	23.4	
33.6	34.2	
7	36.1	
11.7	65.6	
14.4	72.1	
42.1	46.7	
43.7	28.9	
36.5	50.9	
20.2	28.5	
23.2	11.9	
39.7	22.8	
28.3	34.2	
15.3	8.2	
24.3	30.9	
35.6	20.6	
20.9	18.8	
29	13	
18.7	11	

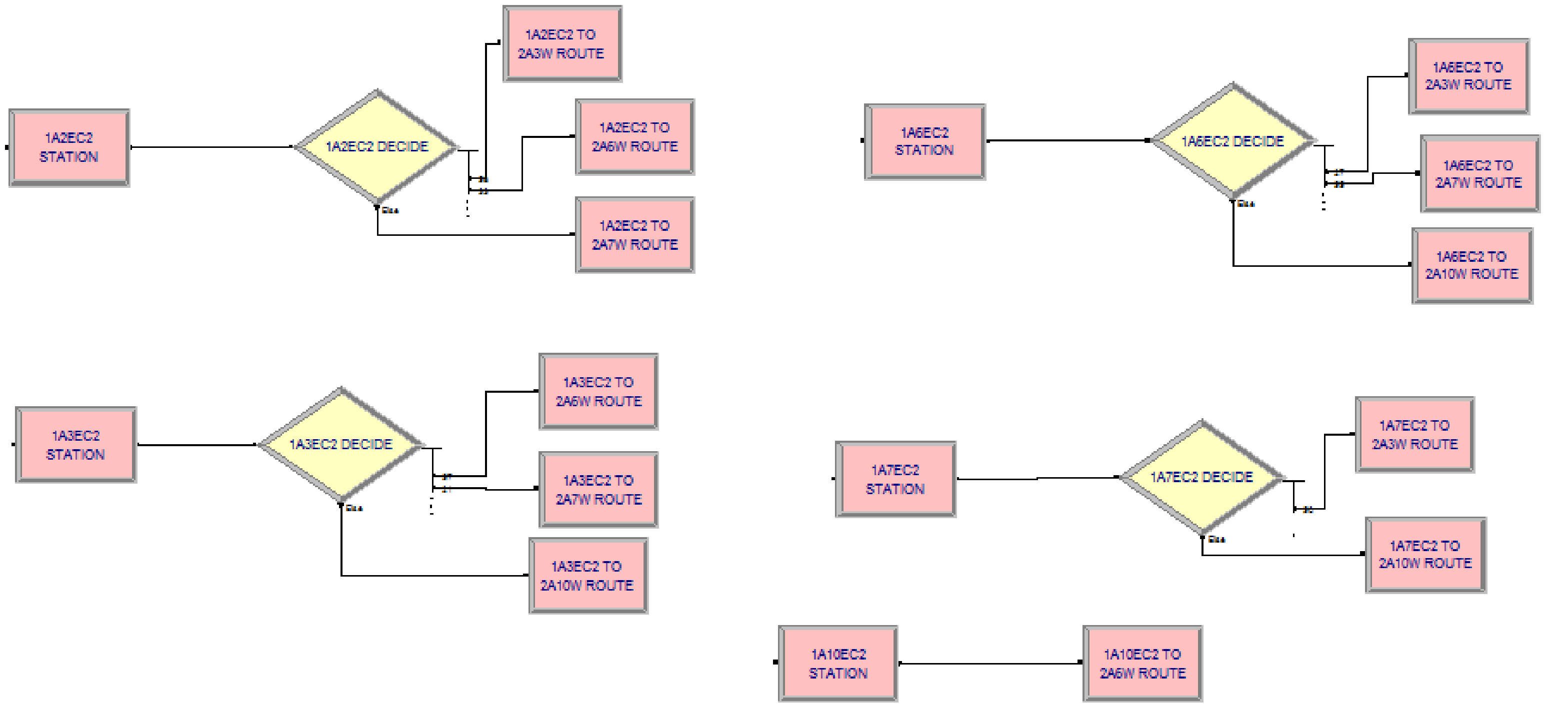
Appendix C. Recorded Station Distances

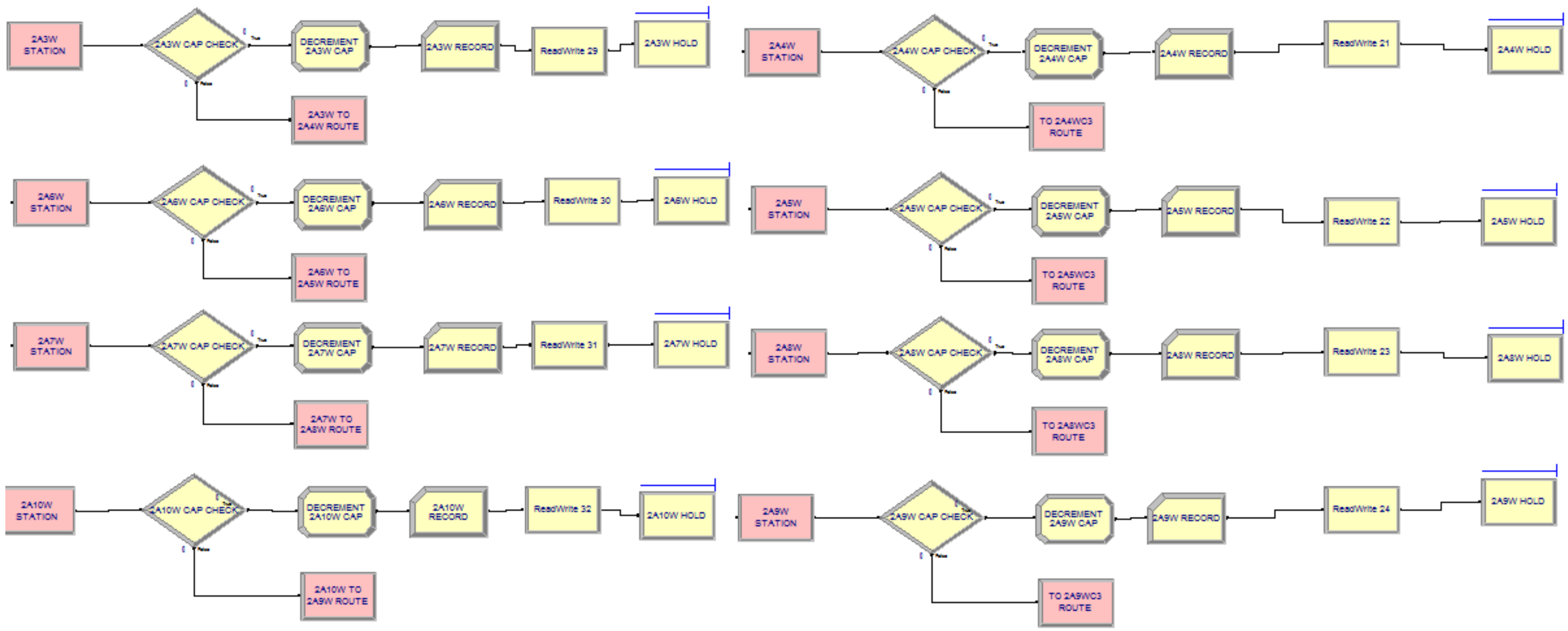
Departing Station	Arriving Station	Distance (Feet)	Departing Station	Arriving Station	Distance (Feet)	Departing Station	Arriving Station	Distance (Feet)
E	1	96	4	11	430	10	9	99
E	4	156	4	E	156	10	2	425
E	5	216	5	6	126	10	3	364
E	8	279	5	1	289	10	6	301
E	9	352	5	4	232	10	7	239
E	11	416	5	8	232	10	11	251
E	2	222	5	9	300	10	E	447
E	3	281	5	11	364	11	1	490
E	6	342	5	E	216	11	4	430
E	7	405	6	5	126	11	5	364
E	10	447	6	2	289	11	8	308
1	2	126	6	3	232	11	9	244
1	4	232	6	7	232	11	2	503
1	5	289	6	10	301	11	3	445
1	8	355	6	11	380	11	6	380
1	9	422	6	E	342	11	7	319
1	11	490	7	8	126	11	10	251
1	E	96	7	2	355	11	E	416
2	1	126	7	3	289	E	1	96
2	3	232	7	6	232	E	4	156
2	6	289	7	10	239	E	5	216
2	7	355	7	11	319	E	2	222
2	10	425	7	E	405	E	8	279
2	11	503	8	7	126	E	3	281
2	E	222	8	1	355	E	6	342
3	2	232	8	4	289	E	9	352
3	4	126	8	5	232	E	7	405
3	6	232	8	9	240	E	11	416
3	7	289	8	11	308	E	10	447
3	10	364	8	E	279			
3	11	445	9	10	99			
3	E	281	9	1	422			
4	3	126	9	4	367			
4	1	232	9	5	300			
4	5	232	9	8	240			
4	8	289	9	11	244			
4	9	367	9	E	352			

Appendix D. Base Model Logic (Full)

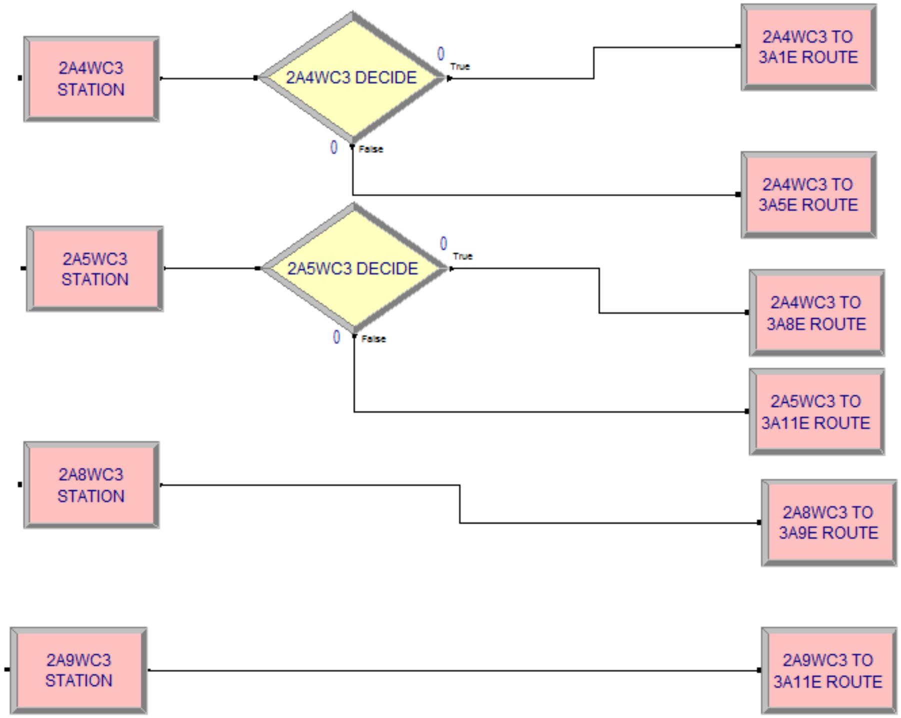


Appendix D (Continued)




2A3W STATION
2A3W CAP CHECK
DECREMENT 2A3W CAP
2A3W RECORD
ReadWrite 29
2A3W HOLD
2A3W TO 2A4W ROUTE
2A4W STATION
2A4W CAP CHECK
DECREMENT 2A4W CAP
2A4W RECORD
ReadWrite 21
2A4W HOLD
TO 2A4WC3 ROUTE
2A6W STATION
2A6W CAP CHECK
DECREMENT 2A6W CAP
2A6W RECORD
ReadWrite 30
2A6W HOLD
2A6W TO 2A5W ROUTE
2A5W STATION
2A5W CAP CHECK
DECREMENT 2A5W CAP
2A5W RECORD
ReadWrite 22
2A5W HOLD
TO 2A5WC3 ROUTE
2A7W STATION
2A7W CAP CHECK
DECREMENT 2A7W CAP
2A7W RECORD
ReadWrite 31
2A7W HOLD
2A7W TO 2A8W ROUTE
2A8W STATION
2A8W CAP CHECK
DECREMENT 2A8W CAP
2A8W RECORD
ReadWrite 23
2A8W HOLD
TO 2A8WC3 ROUTE
2A10W STATION
2A10W CAP CHECK
DECREMENT 2A10W CAP
2A10W RECORD
ReadWrite 32
2A10W HOLD
2A10W TO 2A9W ROUTE
2A9W STATION
2A9W CAP CHECK
DECREMENT 2A9W CAP
2A9W RECORD
ReadWrite 24
2A9W HOLD
TO 2A9WC3 ROUTE

Appendix D. (Continued)



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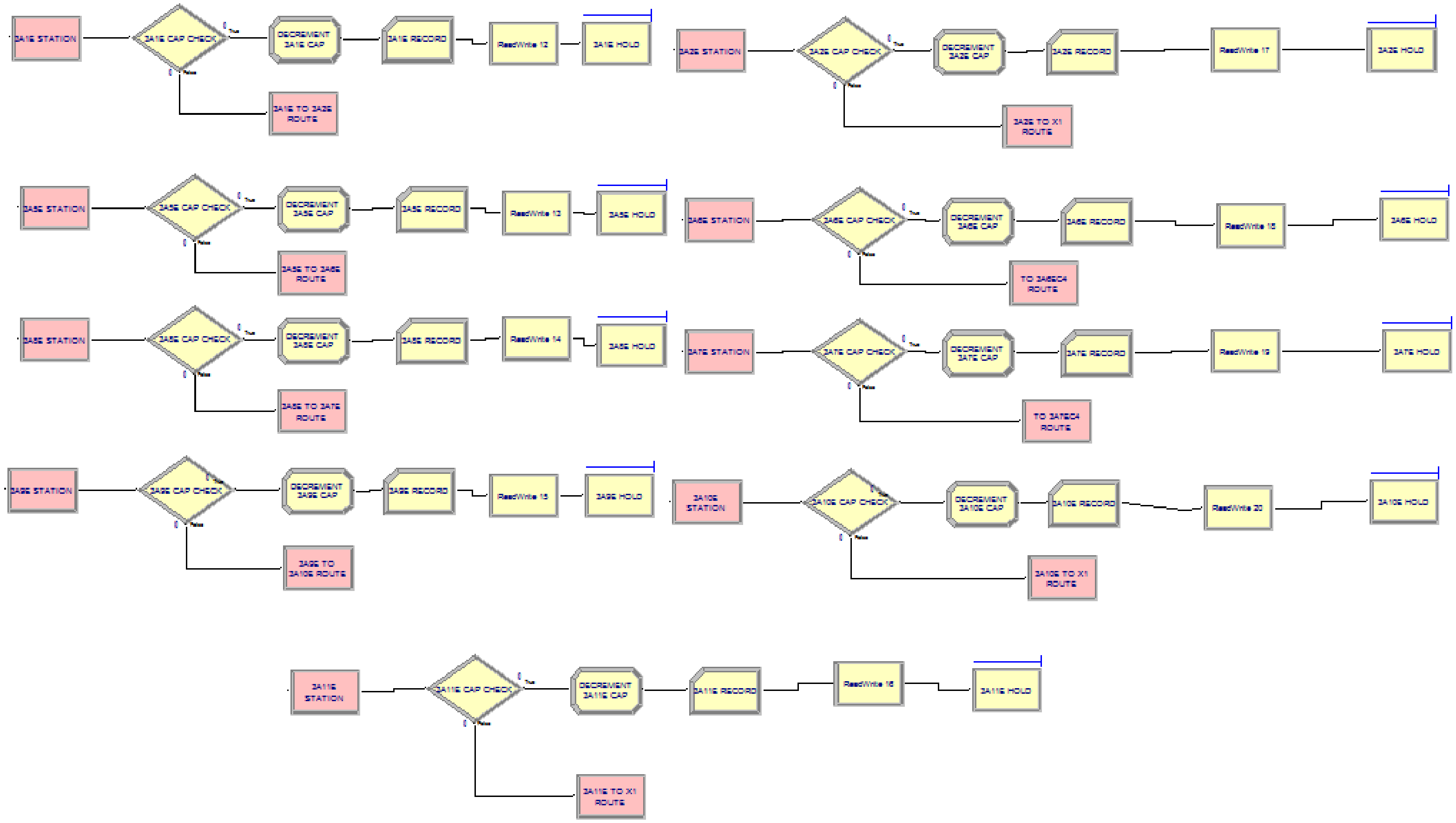

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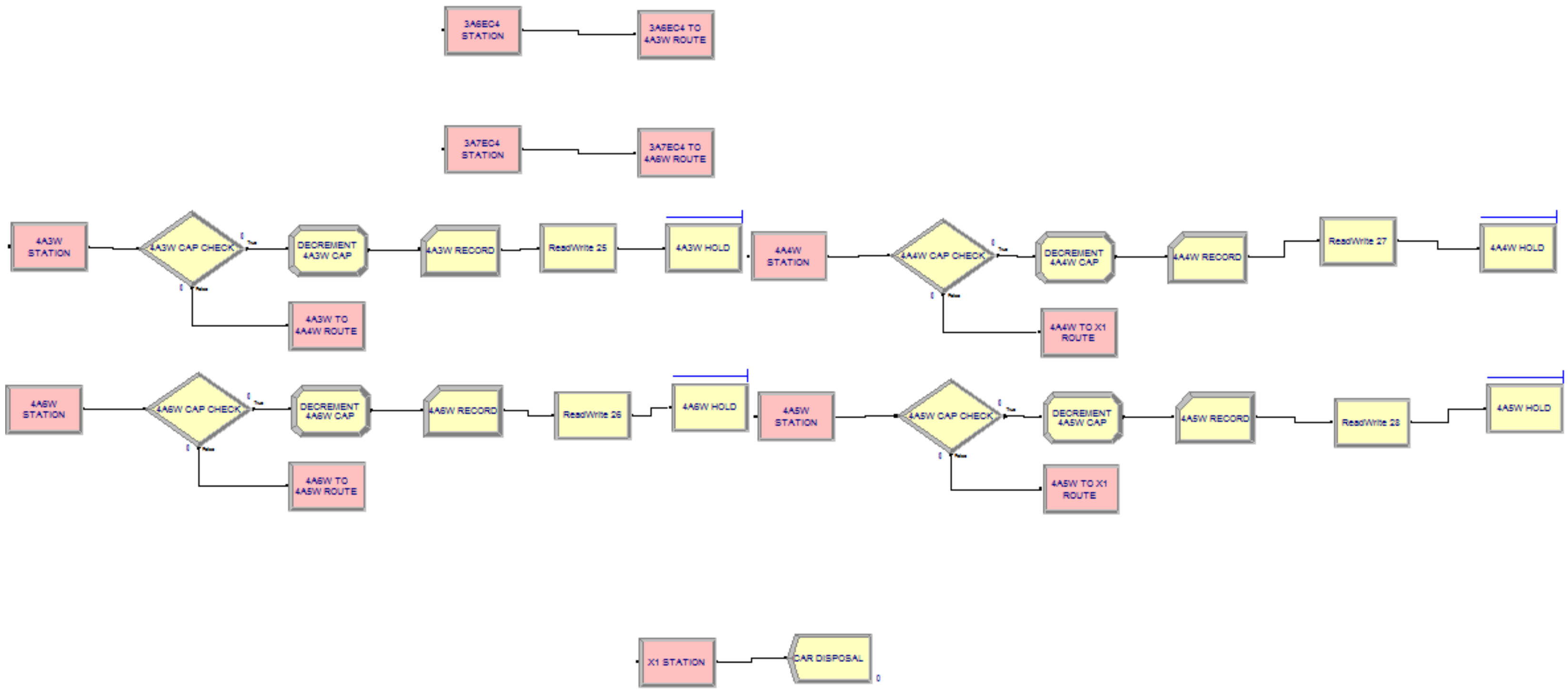
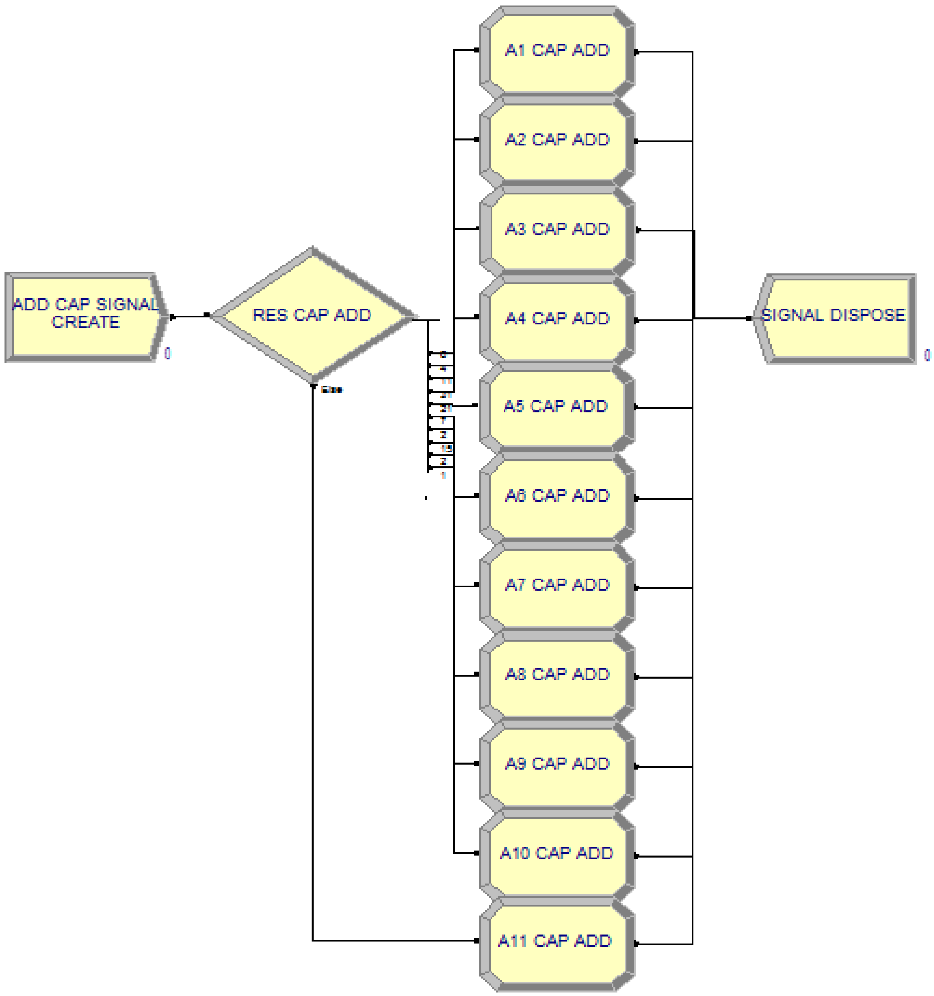


Appendix D. (Continued)



Appendix E. Experimental Model Logic (Full)