

**Proactive Decision Support Tools for National Park and Non-Traditional Agencies
in Solving Traffic-Related Problems**

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ABSTRACT

Transportation Engineers have recently begun to incorporate statistical and machine learning approaches to solving difficult problems, mainly due to the vast quantities of data collected that is stochastic (sensors, video, and human collected). In transportation engineering, a transportation system is often denoted by jurisdiction boundaries and evaluated as such. However, it is ultimately defined by the consideration of the analyst in trying to answer the question of interest.

In this dissertation, a transportation system located in Jackson, Wyoming under the jurisdiction of the Grand Teton National Park and recognized as the Moose-Wilson Corridor is evaluated to identify transportation-related factors that influence its operational performance. The evaluation considers its unique prevalent conditions and takes into account future management strategies. The dissertation accomplishes this by detailing four distinct aspects in individual chapters; each chapter is a standalone manuscript with detailed introduction, purpose, literature review, findings, and conclusion. Chapter 1 provides a general introduction and provides a summary of Chapters 2 – 6. Chapter 2 focuses on evaluating the operational performance of the Moose-Wilson Corridor's entrance station, where queueing performance and arrival and

probability mass functions of the vehicle arrival rates are determined. Chapter 3 focuses on the evaluation of a parking system within the Moose-Wilson Corridor in a popular attraction known as the Laurance S. Rockefeller Preserve, in which the system's operational performance is evaluated, and a probability mass function under different arrival and service rates are provided. Chapter 4 provides a data science approach to predicting the probability of vehicles stopping along the Moose-Wilson Corridor. The approach is a machine learning classification methodology known as "decision tree." In this study, probabilities of stopping at attractions are predicted based on GPS tracking data that include entrance location, time of day and stopping at attractions. Chapter 5 considers many of the previous findings, discusses and presents a developed tool which utilizes a Bayesian methodology to determine the posterior distributions of observed arrival rates and service rates which serve as bounds and inputs to an Agent-Based Model. The Agent-Based Model represents the Moose-Wilson Corridor under prevailing conditions and considers some of the primary operational changes in Grand Teton National Park's comprehensive management plan for the Moose-Wilson Corridor. The implementation of an Agent-Based Model provides a flexible platform to model multiple aspects unique to a National Park, including visitor behavior and its interaction with wildlife. Lastly, Chapter 6 summarizes and concludes the dissertation.

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GENERAL AUDIENCE ABSTRACT

In this dissertation, a transportation system located in Jackson, Wyoming under the jurisdiction of the Grand Teton National Park and recognized as the Moose-Wilson Corridor is evaluated to identify transportation-related factors that influence its operational performance. The evaluation considers its unique prevalent conditions and takes into account future management strategies. Furthermore, emerging analytical strategies are implemented to identify and address transportation system operational concerns.

Thus, in this dissertation, decision support tools for the evaluation of a unique system in a National Park are presented in four distinct manuscripts. The manuscripts cover traditional approaches that breakdown and evaluate traffic operations and identify mitigation strategies. Additionally, emerging strategies for the evaluation of data with machine learning approaches are implemented on GPS-tracks to determine vehicles stopping at park attractions. Lastly, an agent-based model is developed in a flexible platform to utilize previous findings and evaluate the Moose-Wilson corridor while considering future policy constraints and the unique natural interactions between visitors and prevalent ecological and wildlife.

Dedication

To my parents Rosa Fuentes and Ernesto Fuentes, for being the rock and loving me unconditionally. To my wife Indhira Hasbun, for putting up with my roller coaster of emotions, the good and the bad. I know I can always count on you and I love you. To my siblings Ernesto, Osvaldo, and Edith for always being there and reminding me who I am. To my growing family, Rachel Fuentes and Lili Fuentes. Julia Shahilys Baez Guerrero, Douglas Miguel Hasbun Jose, Sabrina Marcelle Hasbun Baez, Amin Abel Hasbun Gena, Rosanna Melo-Hasbun, Douglas Hasbun. To my longtime friends Andrew Christensen, Cole Lovell, and Kirk Jackson who are always on my mind. I love you all, and you have all played a bigger role in this accomplishment than you can ever imagine.

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1 CHAPTER 1: INTRODUCTION

The discipline of Civil Engineering is in an era where multidisciplinary solutions to current, and future problems require quick adaptation to advanced technology and computation resources. The branch of Transportation Engineering under the discipline of Civil Engineering is in a unique position as the management and operations of transportation systems require quick and confident decision making in an ever-changing world. Transportation system decisions impact the road users immediately while infrastructure decisions are made to prepare for the anticipated future. Each decision is made after careful consideration and evaluation of obtained data, prevailing conditions and predicted future conditions.

Transportation data is collected in various formats ranging from electronic counters, inductive loop detectors, video monitoring, video recording, electronic sensors, and human on-site data collection. At present, new fields encompass interdisciplinary approaches to collecting, managing and analyzing of data to find fast and useful solutions with the application of computational technologies. The field of transportation engineering along with the emerging fields of urban computing and data science are in a distinctive position to take advantage and apply advanced analytical solutions to large quantities of data that are becoming available in the urban setting.

Urban settings, however, are not a requirement for implementing advanced analytical methodologies and solving transportation system solutions. Smaller scale systems and networks can implement the same methodologies to identify solutions to their systems, some methodologies such as machine learning which encompass statistical, classification and Bayesian

inference methodologies acknowledge that there are two regimes: one where much data is available and the other, where little data is available (*Downey 2013*).

This research focuses on demonstrating applications of transportation system solutions and data science methodologies in a National Park transportation system setting. The objective is to illustrate how available data can be extended to determine prevalent transportation system operational performance, to prepare and plan for future transportation system changes and to illustrate applicable methodologies and development of tools to solve common transportation system scenarios. One such tool for extending available data is Agent-Based Modelling (ABM) by providing a platform capable of generating synthetic data of prevailing conditions and capability to test alternatives. Its use in a National Park setting fits as it can capture the unique environment present in such a setting (wildlife, site-seeing, time-dependent attractions) and allows for the direct instruction of agents to behave and interact with their environment in terms of what is observed in the real world.

The desired outcome for this dissertation is that it will serve as a reference to illustrate approaches for National Park Service managers as well as non-traditional agency professionals. This thesis illustrates the process to examine and implement proactive strategies for managing transportation system operations with various strategies. This is hoped to be achieved through the breakdown of methodologies which guides the National Park Service and non-traditional agencies to utilize similar methods to solve local or network-wide transportation issues. The methods are applied in the unique setting of a National Park which adds a consideration to the types of constraints and behaviors observed, but ultimately the fundamentals behind the applied methods remain the same and applicable to appropriate cases.

The work presented in this dissertation identifies some of the unique operations experienced in a National Park. Chapter 2 and Chapter 3 describe in detail the procedure to evaluate a fundamental aspect of traffic operations which is the queueing of vehicles and delay expectations. In Chapter 4, the evaluation of GPS-tracks is used to identify the probability of vehicles stopping along the MWC and explore machine learning methodology. Chapter's 2 – 4 build the foundation to Chapter 5, where the operations and findings from the previous studies are implemented in an ABM. The application of ABM in a National Park setting provides a flexible platform to incorporate various aspects that are unique to such a setting. These include the unique visitor behavior encountered in a National Park where the delay is a lower priority, the interaction with wildlife and the interest of slow travel and sightsee along a corridor.

Furthermore, this dissertation contributes to knowledge of solving transportation system problems with advanced analytical methodologies. As data is becoming easier to obtain and access at a lower-cost, transportation professionals have a responsibility to use the latest data to implement feasible up to date solutions. Taking advantage of analysis methodologies is difficult when the references are in different disciplines. Thus, the dissertation presented here demonstrates traditional and advanced approaches to addressing transportation system problems with available data.

1.1 Research Question

The primary question which this research anticipates to answer is: “How can transportation approaches and data science methodologies be implemented in a non-urban setting to find transportation system solutions and provide tools and guidance to non-traditional professionals?” Answering this question will be addressed through a transportation evaluation of

a National Park Service corridor, the Moose-Wilson Corridor (MWC) is located in Grand Teton National Park. The transportation approaches will consist of implementing various methodologies often used in traffic engineering to evaluate the queueing of vehicles and delay. The data science methodologies consist of machine learning approaches to evaluate GPS-tracks data of the corridor. Those methodologies culminate in an ABM which is a tool capable of modeling the observed behavior of visitors in the MWC and consider the unique interactions that are common in a National Park setting including visitor interaction with wildlife and the natural scenery. Chapter 2 – Chapter 5 construct a big picture context of the MWC transportation system, and how each study provides a building block to a transportation system evaluation.

1.2 Research Problem and General Approach

A possible problem encountered by legacy professionals in civil and transportation engineering or non-traditional agency professionals tasked with transportation-related problems is in taking advantage of available resources and methodologies to solve transportation concerns. Open source tools such as R and Python provide powerful avenues for data collection, management, visualization, and analysis. Additionally, open-source modeling and simulation platforms provide similar benefits in ABM. This research aims to illustrate a data collection process and demonstrate traditional and advanced analytic solutions and tool development for solving transportation system issues. Additionally, a unique contribution presented by this work is in emphasizing a National Park transportation corridor where findings from previous studies as well as various interactions not often considered in commercial modeling tools are considered together in a single ABM platform.

The general approach will consist of taking the Moose-Wilson Corridor transportation system, breaking it down into manageable problems and finding solutions. Chapter 2 – 5 are standalone manuscripts that have been or will soon be submitted to publication. Each Chapter contains a detailed introduction, purpose, literature review, findings, and conclusions. In Chapter's 2 – 4, in addition to the main content of the manuscript, an additional section after the chapter's conclusion provides additional detail and discussion into incorporating the respective chapter's methodology and findings into an ABM.

In Chapter 2, the Moose-Wilson Corridor entrance station is evaluated for queueing performance as well as the evaluation of a future entrance station in the opposite end of the corridor. This evaluation consists of utilizing a deterministic approach to analyzing queueing performance as well as a simulation approach which considers stochastic variability. Findings include a sensitivity analysis of anticipated queueing service times and vehicle lengths at current and future entrance stations, under varying arrival rates and service times. Implementing this study in an ABM consists of determining Poisson and deterministic values for vehicle arrival times and entrance gate service times and thus providing park managers information about the variation of measures of performance that can be anticipated from monitoring strategies.

In Chapter 3, a popular attraction along the Moose-Wilson Corridor known as the Laurance S. Rockefeller Preserve is evaluated for queueing performance. The Laurance S. Rockefeller system consists of 54 parking spaces, and Little's Law is implemented to evaluate the system's performance. Findings include an evaluation of the systems performance as well as probability mass functions for varying arrival and service rates of the vehicles in the system. Implementing this study in an ABM consists of identifying the number of vehicles that visit the Laurance S. Rockefeller Preserve and distributing the time spent at this attraction in terms of

time spent parked. Thus, providing park managers information about typical and anticipated use levels.

In Chapter 4, a machine learning approach known as a decision tree analysis is implemented to evaluate the probability of vehicles stopping along different attractions in the Moose-Wilson Corridor. GPS tracking data is utilized to determine start origins, end destinations, and stops along the corridor. Findings include the generation of decision trees and confusion tables that provide accuracies of the decision tree models. Implementing this study in an ABM consists of interpreting each of the decision tree model results to capture the behavior of vehicles that made multiple stops while traveling through the Moose-Wilson Corridor. Thus, the results provided the probability that a vehicle would stop at an attraction, and subsequently if they would stop at another attraction. Therefore, these probability values were directly used as rules to guide the agents through the Moose-Wilson Corridor.

In Chapter 5, a tool is developed and utilized which applies Bayesian methods combined with an ABM simulation. The tool is constructed to evaluate a desired management strategy for the Moose-Wilson Corridor. Key findings include an estimation of the time of day a 200-vehicle capacity will be reached in the Moose-Wilson Corridor. The time of day information allows management to evaluate if the capacity is reached when certain levels of visitor's arrivals are observed and allows for preparation and consideration of management alternatives if capacity is reached. Thus, this chapter illustrates some of the considerations for developing an ABM tool to analyze prevailing conditions and evaluate future changes. Additionally, it highlights the appropriateness of using ABM in a setting where visitor behavior and surroundings are unique.

Lastly, in Chapter 6, a discussion and conclusion of the dissertation are provided.

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2 CHAPTER 2: Evaluating National Park Entrance Station Queues: A Case Study in Grand Teton National Park

This chapter is adapted from Fuentes, A., Heaslip, K., Kidd, A., D'Antonio, A. (*In Review*) Evaluating National Park Entrance Station Queues: A Case Study in Grand Teton National Park. *Case Studies on Transport Policy*

2.1 Introduction

Grand Teton National Park (GRTE) located in Wyoming welcomes local, domestic and international visitors each year. Aside from its dominant presence in the preserved lands of the west, GRTE exceptionally captures the sense of nature, freedom, and wilderness in the Teton mountain range that each visitor is sure to appreciate. GRTE's prominence can be observed by recreation visits over 2.5 million during 2013 and 2014, and surpassing 3.25 million in 2016 (*National Park Service 2016a*). With such a large number of recreation visits, GRTE officials and staff are challenged to be effective in communicating essential park information, answering questions and completing additional responsibilities. Entrance stations and visitor centers are the first points of contact for many new and returning visitors. Thus they function as resource hubs by providing information to visitors.

In GRTE's current management policy, three entrance stations cover the area of approximately 1,256 square kilometers. These stations consist of the Granite Canyon entrance, the Moose entrance, and the Moran Junction entrance (*National Park Service 2016b*). Entrance stations at GRTE serve to collect fee payments, distribute park information and inform incoming visitors of other special items. Likewise, entrance stations provide visitors the opportunity to ask

questions and are advised about optimizing their trip experience. Overall, current GRTE entrance station policies serve as a positive element for the daily management of operations and park objectives. However, entry stations by nature can result in long wait times if the demand for visitor arrivals is high or the entrance station service time has high variation. When the delay is experienced by the interaction of high vehicle arrivals and high service times, system operations and staff can become overwhelmed resulting in negative visitor perception and a possible decline in visit satisfaction.

Additional considerations by GRTE officials included the operations of the corridor in which the entrance station is located as well as its nearby surroundings. Therefore, system operations at entrance stations may be of importance when taking into consideration the temporal variation of traffic upstream and downstream of the entrance gate. Similarly, system operations of an entrance station can affect nearby or adjacent locations. Queueing of vehicles that span a long distance create congestion and can result in adverse impacts to nearby road facilities and establishments.

The primary objective of this paper is to provide reference and guidance on evaluating queuing measures of performance at entrance stations and applying the results to current and future policies at National Parks. The policy implications this study intends to address is concentrated on the management of entrance station performance for existing operations and future planning. When evaluating existing conditions, the policy considerations may be to maintain operations at the desired level or under specified thresholds. When considering future planning, entrance stations effects such as queue length and queue waiting time may need to be considered to minimize the impact to adjacent traffic facilities. The objective will be accomplished by focusing specifically on GRTE's Granite Canyon entrance station as well as the

evaluation of a new future entrance station. Thus, an overview of data collection strategies and computation of performance measures will be emphasized for current and anticipated scenarios. The paper will illustrate the use of queueing theory methodology to gain an understanding of a queueing setting, quantify observations and develop information for policy decision making.

The paper is organized as follows. Section 2 provides a literature review of relevant previous studies. Section 3 describes the case study location, its surroundings, and descriptions of the considered entrance stations. Section 4 specifies how and where the data was collected, provides key assumptions and overviews the collected data. Section 5 specifies the analysis methodology, preliminary findings and later the analysis results and analysis discussion. Section 6 provides a discussion on how the findings relate to policy implications. Lastly, section 7 concludes the paper.

2.2 Literature Review

Specific investigations on queueing characteristics and traffic operations on a single National Park corridor such as the intent of this study have not been of significant focus. Relevant studies on a single National Park corridor include work by Hallo and Manning whose efforts were on the Ocean Drive corridor in Acadia National Park. The authors evaluated carrying capacity and visitor perception when driving in a scenic corridor. In the authors' efforts to evaluate carrying capacity, key differences for the analysis between a National Park road and traditional roadways are identified. Data collection for the corridor was collected through trajectory routes from GPS units and a survey of visitors at the end of their travel. Overall the study focused on an approach to determine social carrying capacity based on visitor perception and prevailing conditions (*Hallo and Manning 2010*). A separate study focused on visitor

interaction with transportation and recreation on the same Ocean Drive corridor in Acadia National Park. In this effort, surveys and interviews helped to identify indicators of quality that factor into visitor experiences when they drive for pleasure in a National Park setting (*Hallo and Manning 2009*). In describing the Ocean Drive corridor, a reference to the entrance station was made in both studies and similarly a common finding that congestion resulted in a negative effect on visitor perception. Although not explicitly stated, as the focus was on evaluation within the corridor, congestion effects can likely be experienced before entering a corridor as visitor's queue to enter through the park entrance station.

Similarly, few studies have been published where the primary focus is on the entrance station of a National Park. Studies published by Upchurch provided insight into service times and capacities for National Parks by focusing on entrance stations in Arches National Park and the south entrance of the Grand Canyon National Park. In his study, Upchurch utilized data processed from the entrance stations fee collection software to determine arrival rates while service time data was collected manually on designated days. The significant contribution this study provided aside from its identification of critical factors affecting service time consisted of the definition of capacity for an entrance station as the “number of vehicles per hour that can be processed in a lane (or lanes)” and its usefulness in the current evaluation and future planning. The study reported an average service time and capacity of 32 seconds and 112 vehicles per hour, respectively, for Arches National Park and average service time and capacity of 37 seconds and 97 vehicles per hour, respectively, for the south entrance station of the Grand Canyon National Park. Overall the study also provided an approach to determine staffing decisions at entrance gates based on the anticipated capacity levels (*Upchurch 2006*). A more recent study by Upchurch provided entrance station findings for Utah's Zion National Park. The study's purpose

was to analyze issues related to transportation at the park, and one of the issues identified was related to Zion National Park's entrance station. Overall, by utilizing historical data and methods identified by the author's previous work, recommendations were provided to the park regarding improvements that would enhance entrance station capacity and operations. The Zion National Park entrance station was reported to have 194 vehicles per hour capacity which results in approximately a 19 second service time (*Upchurch 2015*). The previously discussed studies by Upchurch provided insights into important considerations queueing plays in a National Park setting. By reporting queueing observations and capacities of entrance stations at various National Parks, support for decision making is provided. The studies, however, did not fully maximize queueing theory capabilities such as the evaluation of future operating performance with varying arrival and service rates.

The use of queueing theory is commonly used in operations research and industrial systems, in which the measures of performance are referenced to maximize or minimize the efficiency of a system and then make informed policy decisions. Such an approach was utilized in a study to address the planning of transportation facilities in the Olympic Village in preparation for the 2004 Athens Olympics. In the study, a projected number of visitors based on accommodation capacities were used to estimate design constraints for queue lengths and desired waiting times for parking areas and entrance gate capacities (*Yannis et al. 2009*). Another study utilized queueing methods to make policy decisions on future berth construction projects in the Manila International Container Terminal in the Philippines. In this study queueing theory was utilized by considering historical data of arrival rates, service times and the cost of waiting time for incoming ships. An analysis of base case operations and the consideration of the construction of additional berths found improvements in queueing measures of performance. Ultimately it

was recommended that the current number of berths was adequate after a cost-benefit analysis of the cost of ships waiting in the queue would not surpass the cost of constructing a new berth (*Saeed and Larsen 2016*).

A standard method for evaluating queueing theory in a steady state queueing system is through the use of Little's Law, which defines the relationship that the expected number of units in a queueing system is equivalent to the service time multiplied by the expected wait time in the system (*Little 1961*). Due to its simplistic approach, Little's Law has been used in multiple advanced algorithms and models for system verification. One such application includes the use of Little's Law to verify the accuracy of a proposed model focused on improving the system performance for call centers (*Phung-Duc and Kawanishi 2014*). A more appropriate study which utilizes queueing theory and Little's Law in a National Park setting was performed at the GRTE. In this study, the Laurence S. Rockefeller Preserve (LSR) parking area with 54 spaces was evaluated for queueing measures of performance for a system which saw an arrival rate of approximately 25 vehicles per hour and a service rate (parked time) of 80 minutes. Overall, it was determined by the use of Little's Law that the current facility utilization use was 61%. Findings from this study reported that current operations of the LSR parking were adequate but also provided thresholds and mitigation suggestions for conditions that would stress the system (*Fuentes et al. 2017*).

2.3 Case Study

GRTE's Granite Canyon entrance station is located on the Moose-Wilson Road Corridor (MWC). As can be denoted by its name, the MWC connects the communities of Wilson to the south and Moose to the north. Much of the demand on this corridor can be attributed to its

proximity to Teton Village and the Town of Jackson. Teton Village is a popular resort just outside GRTE boundaries, and the Granite Canyon entrance is located just north of the resort. The Town of Jackson is GRTE's gateway community southeast of the Granite Canyon entrance and GRTE. Teton Village and the Town of Jackson are likely the AM origin and PM destination, respectively, for many park visitors entering through the Granite Canyon entrance. The MWC in GRTE is highlighted by the red dashed line in Figure 2-1.

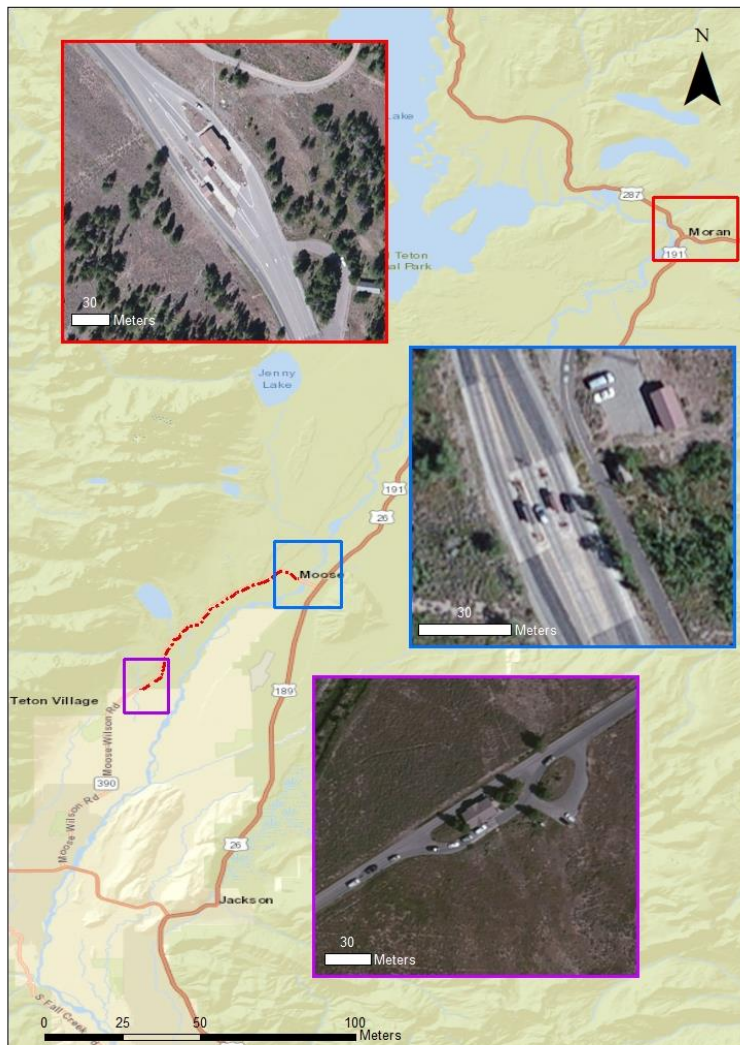


Figure 2-1. GRTE Entrance Stations

Queuing measures of performance at the Granite Canyon entrance as well as consideration of a north entrance station were evaluated. The northern entrance station was considered near the MWC and Teton Park Road intersection in the community of Moose. Consideration of a northern Moose entrance station is in line with GRTE's Moose-Wilson Corridor Comprehensive Management Plan, and Environmental Impact Statement (Final Plan/EIS) released in August of 2016 (*National Park Service 2016d*). The most notable impacts to the MWC's entrance station performance will be seen by the introduction of a northern queueing station and limiting the MWC capacity to 200 vehicles at a time (*National Park Service 2016c*). Thus, this study provides an excellent case study as the use of queueing theory methodology provides future policy guidance.

The procedure provides a repeatable approach for assessing current queuing operations at an entrance station. Additionally, the results can provide support for addressing safety concerns imposed by the policy change of introducing queuing at a new location, in this study the Moose end of MWC is the new location where queuing will be introduced. The utilized method of evaluation is capable of being extended for current, and future policy evaluations at other National Park's and protected area settings, or any situation in general where queuing is or may be observed.

2.4 Description of Entry Stations

The study range extended the length of the MWC within the GRTE boundaries and consisted of collecting volume arrival data at the Granite Canyon entrance in the southern section of the MWC as well as a collection in the northern section of MWC. There is a benefit in describing the two additional entrance stations of GRTE to illustrate their varying queuing

characteristics. The standardized format of describing a system's queuing characteristics is to define the arrival process type/service process type/number of servers (*Teodorovic and Janic 2016*). The labeling of arrivals and departures is achieved by describing their distribution. The most common for vehicle arrivals is the Poisson distribution and is denoted by the letter *M*. A constant and deterministic arrival is denoted by the letter *D*. Due to the randomness in vehicle arrivals and departure after service time, each entry station within GRTE can be described by a Poisson distribution (*M*). The alternative would be that the number of arrivals is known before they arrive and would be denoted by the letter *D*. Each of the GRTE entrance station arrivals and departures can be assumed to fall under the Poisson arrival distribution. However, the number of servers differ between GRTE entrance stations.

The Granite Canyon entrance consists of a single station, one entry lane and one exit lane. As vehicles arrive, some may need to purchase a pass, others may have inquiries regarding park activities, or a combination of both events may take place. Vehicles that have a pass are still required to stop and show their pass to GRTE staff to proceed. Therefore, due to its single window and constraint of serving only one vehicle at a time, the Granite Canyon entrance can be defined as an *M/M/1*, first come first served (FCFS) queue (*Taha 2007*). Figure 2-1 illustrates an aerial image from ESRI's ArcGIS of the Granite Canyon entrance, Moose Entrance, and Moran Junction Entrance to be referenced for comparison. In the figure, the bottom frame illustrates the Granite Canyon entrance (*M/M/1*), the middle frame illustrates the Moose Entrance (*M/M/2*) and the top frame illustrates the Moran Junction Entrance (*M/M/3*).

The Granite Canyon entrance is a system and queues are generated within the system. Figure 2-2, an aerial image obtained from ESRI's ArcGIS, illustrates how these terms apply to the Granite Canyon entrance station. The overall evaluation of the Granite Canyon entrance will

consist of analysis results for the system and the queue, as was similarly accomplished by Fuentes et al. for parking at the Laurence S. Rockefeller Preserve also on the MWC (Fuentes et al. 2017). The significant values that are expected to be determined are the estimation of average queue length and queue waiting time, for the system and the queue. The queue length is the number of vehicles waiting to be served, while the queue waiting time is the amount of time spent waiting to be served. When estimating the queue length and queue are waiting time in the system, vehicles that are in the queue, as well as those in service, are considered. When determining queue length or queue waiting time in the queue, only the vehicles that are waiting in the queue are considered. Therefore, results for the system will always be higher than the results for the queue. Figure 2-2 illustrates the Granite Canyon entrance system, where seven vehicles are in the system, and six vehicles are in the queue.

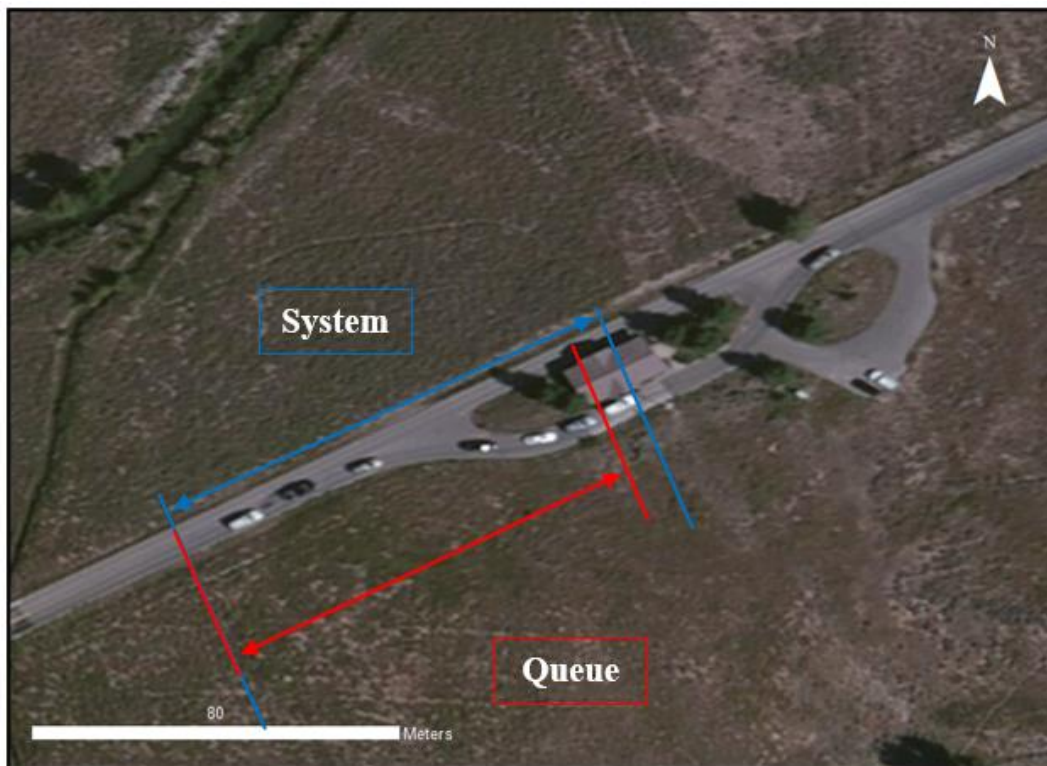


Figure 2-2 Granite Canyon Entrance Station

2.5 Data Collection and Assumptions

Data was collected by the use of data collection cameras for 21 days as part of a suite of data collected for the development of the Moose-Wilson Corridor Comprehensive Management Plan (*Monz et al. 2014; Monz et al. 2015*) during three days in August of 2013, and the remainder between June – October of 2014. Data were collected within 13 hours, from 7:00 AM – 8:00 PM on sampling days. Study dates and times were selected to achieve a stratified random sample of visitor arrivals.

The first set of data was collected at the Granite Canyon entrance station, while the second set of data was captured at the Moose end of the MWC, near the intersection with Teton Park Road. Data consisted of vehicle counts and a time stamp at each location. The volume of arriving vehicles was observed at the Granite Canyon entrance, and the volume of vehicles driving towards Granite Canyon entrance was recorded on the northern portion of MWC.

The equipment for the Granite Canyon entrance was set-up adjacent to the entrance station window and counted vehicles as they departed the entrance station. Vehicles would be counted after they had been served and were accelerating out of the entrance station approximately 21 meters downstream of the station facility. Thus, data for the service rate of park employees (servers) at the entrance station window was not directly recorded. A similar approach was taken in capturing the volume at the northern Moose end. This volume is of primary interest as the southwest-bound vehicles entering the MWC would be affected by the implementation of the new queueing station. Figure 2-3 highlights the area in which the Moose end volumes were collected, and where the equipment was set to capture the southwest-bound

volume. In Figure 2-3 the red square illustrates the area where the data was collected along the MWC, the yellow circle illustrates the intersection of MWC and Teton Park road.



Figure 2-3 Moose End MWC Data Collection Location

In addition to volume collected at the Granite Canyon entrance, vehicle headway was a derived attribute that was related to service time. The vehicle headway is the amount of time that separates two vehicles while traveling. Thus, references to similar studies, assumptions, and engineering judgment were used to interpret the service rate at the Granite Canyon entrance station. Research conducted by Upchurch determined the capacity of 112 vehicles per hour for Arches National Park and 97 vehicles per hour for the Grand Canyon National Park south entrance, resulting in service times of 32 seconds and 37 seconds respectively (*Upchurch 2006*). Additionally, Upchurch also determined a capacity of 194 vehicles per hour at Zion National

Park resulting in service times of approximately 19 seconds (*Upchurch 2015*). The most critical assumption was assuming the service rate to be the headway. In cases where the visitor arrival rate is significant, assuming the average headway is equal to the average service rate can be a reasonable estimate. The logic behind this assumption is evident when considering a queue that is in place, the time taken for a vehicle to leave the entrance station after being served to the point where the data is being collected becomes a steady state. This, however, can only be inferred when there is high confidence that a queue was in place, such as the peak hours of a high-volume day. Additionally, for the first assumption to be considered a second assumption is made that vehicles accelerate at the same rate after being served. The previous two assumptions were vital in determining the service rate but were also unique to the Granite Canyon entrance system. The final assumption consisted of utilizing service rate values estimated from the Granite Canyon entrance system as anticipated values for the northern Moose end queueing station system.

2.6 Overview of Collected Data

The arrival rate of the visitors passing through the Granite Canyon entrance and the southwest-bound vehicles at the Moose end was the primary set of data referenced and utilized. For the year of 2013, only three days of data were collected in August. For the year 2014, 18 days of data were collected between June – October. The obtained data was allotted into 15-minute bins throughout the daily study period. This allowed for the peak hour to be determined with greater precision. Through reference to the peak hour volumes, the average arrival rate was determined for both the Granite Canyon entrance station and the considered Moose queueing station. The vehicle headway was referenced only for the Granite Canyon entrance and utilized

as the service rate throughout the Moose entrance station calculations. Figure 2-4 illustrates the average vehicle volume observed at the Granite Canyon entrance between August 2013 and June – October of 2014, during the 13-hour data collection period. The highest vehicle arrival rate was observed on August 5, 2013, at 143 vehicles per hour between 9:30 AM – 10:30 AM. The largest average peak hour volume for an entire day was observed on August 3, 2013, with an average of 82.3 vehicles per hour. As Figure 2-4 illustrates, the highest volumes at the Granite Canyon entrance station were mainly seen during the morning hours.

Figure 2-5 illustrates the average vehicle volume observed at the Moose in August of 2013 and June – October of 2014, during the 13-hour data collection period. The highest vehicle arrival rate was observed on August 4, 2013, at 151 vehicles per hour between 3:15 PM – 4:15 PM. The largest average peak hour volume for an entire day was also observed on August 4, 2013, with an average of 87.0 vehicles per hour. As Figure 2-5 illustrates, the highest volumes at the Moose were mainly seen in the afternoon & early evening hours.

By observing Figures 2-4 and 2-5, a distinction can be made about the MWC's visitor demand. Visitors appear to begin their day entering GRTE at the Granite Canyon entrance between the hours of 8:00 AM – 11:00 AM, and re-enter MWC at the Moose between 1:30 PM – 5:30 PM. This relationship suggests that entering vehicles travel straight through the corridor for activities beyond the MWC, and likely exit the park by traveling through the MWC later in the day. Therefore, it is reasonable to assume that the queueing measures of performance experienced in the Granite Canyon entrance during the morning hours would be comparable to what will be experienced in the evening hours at the Moose queueing station. Therefore, similar assumptions were made for both locations when implementing queueing theory to estimate measures of performance.

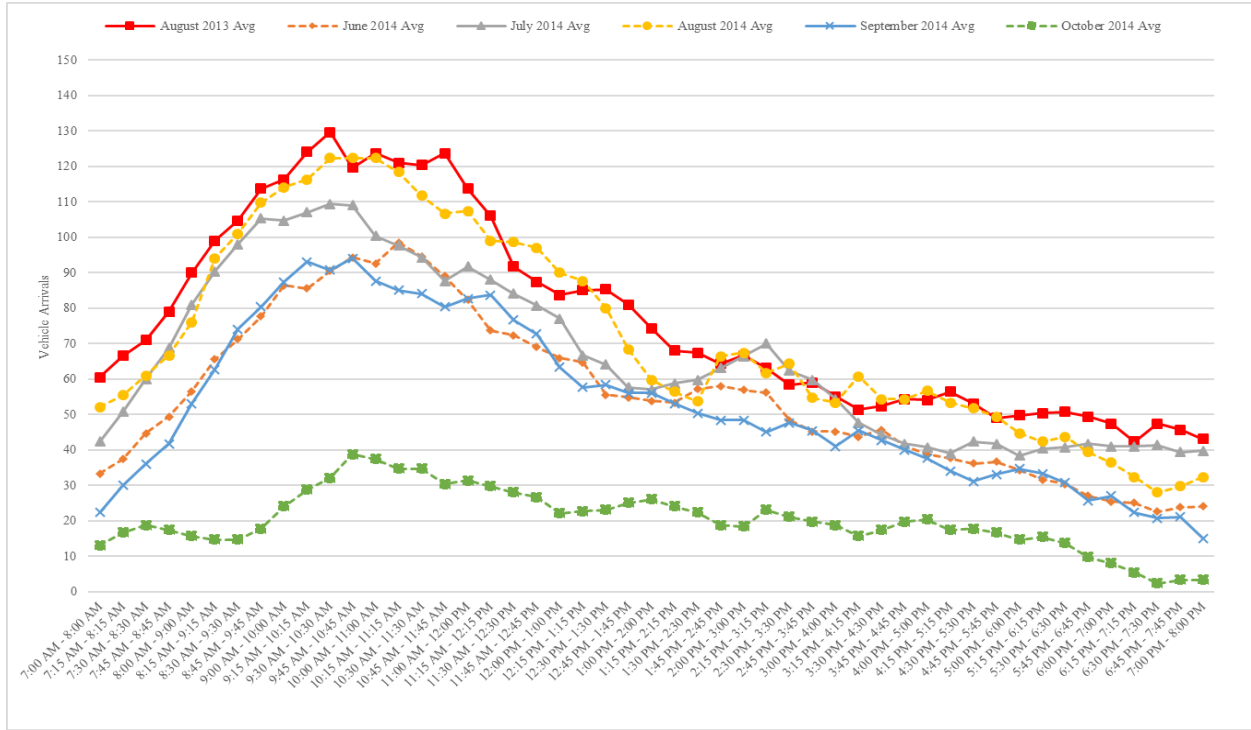


Figure 2-4 Observed Volume at Granite Canyon Entrance Station

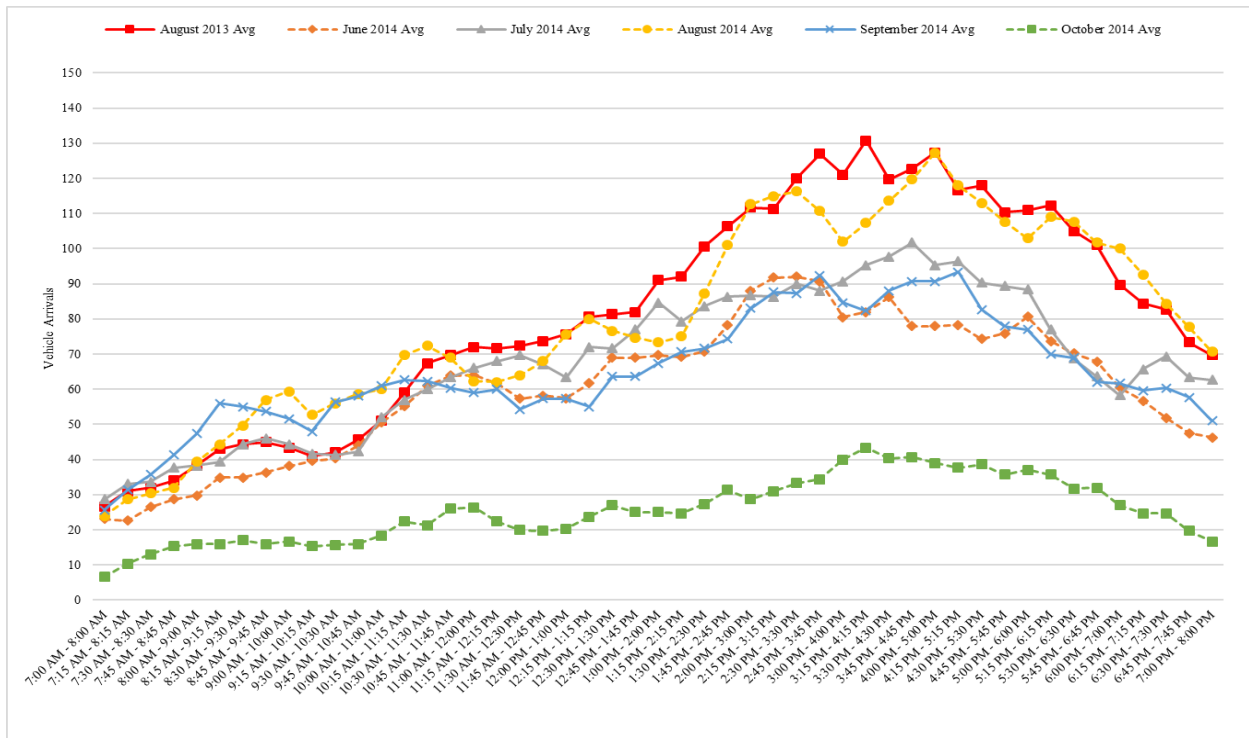


Figure 2-5 Observed Volume at the Moose

A comparison can be made to traffic count data published by the National Park Service (NPS) IRMA Portal to address the appropriateness of the collected data (*National Park Service 2016b*). The portal provides aggregated monthly volume counts for vehicles entering the Moose-Wilson entrance, which is what this study refers to as the Granite Canyon entrance. Table 2-1 illustrates how the data provided by the NPS compares to what was observed in the field in terms of a percent difference. In Table 2-1, the observed monthly values were estimated by multiplying the average 13-hour period volume collected for the days in each month and multiplied by the total days in that month. Thus, there is some error present in the observed volumes reported than what is reported by NPS IRMA portal, but the collected data likely catches the majority of the peak volume from 7:00 AM – 8:00 PM.

Table 2-1 Comparison of 13-Hr Collected Data to NPS IRMA Portal

Month	Collected/ Estimated			NPS IRMA Portal	% Difference
	13-Hr Avg.	Days in Month	Avg. Est Monthly Total		
August, 2013	960	31	29,760	33,877	13%
June, 2014	695	30	20,850	26,879	25%
July, 2014	834	31	25,864	35,362	31%
August, 2014	912	31	28,272	33,045	16%
September, 2014	656	30	19,680	19,667	0%
October, 2014	253	31	7,833	9,195	16%

2.7 Analysis Methodology and Preliminary Findings

Two analysis approaches were utilized to evaluate the queue at both locations of interest in the MWC. The first approach consists of utilizing Little’s Law for a single server model to determine critical parameters capable of measuring the performance of the system. By utilizing the observed values of average arrival rate λ , and the average service rate μ the traffic intensity ρ can be determined. Then the average measures of performance can be determined by the expected number of visitors in the system L_s , expected number of visitors in the queue L_q , expected waiting time in the system W_s , expected waiting time in queue W_q and the expected number of busy servers c' (where c is the available number of servers) which leads to identifying the facility utilization value. The following Equations 2.1 – 2.8 illustrate how these parameters are determined, as well as determining the probability of any “n” number of vehicles in the system (*Taha 2007*).

$$\rho = \frac{\lambda}{\mu} \quad \text{Eq. 2.1}$$

$$L_s = \frac{\rho}{1-\rho} \quad \text{Eq. 2.2}$$

$$L_q = \lambda \cdot W_q = \frac{\rho^2}{1-\rho} \quad \text{Eq. 2.3}$$

$$W_s = \frac{L_s}{\lambda} = \frac{1}{\mu(1-\rho)} = \frac{1}{\mu-\lambda} \quad \text{Eq. 2.4}$$

$$W_q = W_s - \frac{1}{\mu} = \frac{\rho}{\mu(1-\rho)} \quad \text{Eq. 2.5}$$

$$c' = L_s - L_q = \rho \quad \text{Eq. 2.6}$$

$$\text{Facility Utilization} = \frac{c'}{c} \quad \text{Eq. 2.7}$$

$$p_n = (1 - \rho)\rho^n, n = 1, 2, \dots (\rho < 1) \quad \text{Eq. 2.8}$$

It must be noted that the above equations are valid under steady-state queuing conditions. A steady state condition is determined when the service rate μ , is greater than the arrival rate λ . As defined by Little, “under steady-state conditions, the average number of items in a queueing system equals the average rate at which items arrive multiplied by the average time that an item spends in the system” (*Chhajed et al. 2008*). The second approach consists of running some simulations for the *M/M/1* queue at the Granite Canyon entrance and Moose end of the corridor. This analysis is different in the sense that the randomness of the Poisson distribution can be directly applied to the vehicle arrival rate and service time. Thus, the results for length and waiting time differ after each simulation allowing for variation in the results and an idea of the expected range of performance measures. Also, the simulation procedure provides more reasonable estimates for unstable cases that Little’s Law deterministic nature may overestimate.

The critical step taken in achieving the simulation is utilizing the exponential distribution and generated random numbers to determine the vehicle inter-arrival times as well as the service time for each vehicle. Equation 2.9 illustrates the exponential distribution function. A generated random number R is set as the variable $F(t)$. The next step is solving for time t , which will determine the vehicle's inter-arrival time and similarly the service time (*Taha 2007*).

$$F(t) = \int_0^t \lambda \cdot e^{-\lambda x} dx = 1 - e^{-\lambda t}, t > 0 \quad \text{Eq. 2.9}$$

Next, to determine the values of arrival rate λ , and the service rate μ from the previously discussed data, the following steps were taken. First, because the interest was to evaluate the conditions where the queue has a more significant effect, the arrival rate from the day which saw the highest average arrivals is used. Second, the headway between vehicles during peak hours was utilized as the service rate. Following the estimation of the arrival rate and the service rate, the evaluation of the queue can be conducted. Table 2-2 and Table 2-3 illustrate the data required to proceed with the queueing evaluation for the Granite Canyon entrance station and the Moose end proposed queueing station.

In Table 2-2, the highlighted rows denote the times where the most significant amount of vehicle arrivals were observed. Thus, these are the cases where it can be almost sure that the vehicle headway most closely resembles the Granite Canyon entrance service rate. Therefore, the assumption for the evaluation of the queue would have an average service rate of 83 vehicles per hour (referencing 8/4/2013 average day arrivals). The average service rate varied between 25 – 27 seconds but mainly remained below the 30-second mark under higher vehicle arrivals. These service rates are in the range of what was observed by Upchurch in the previously discussed

National Park entrance station studies (*Upchurch 2006; Upchurch 2015*). Similarly, Table 2-3 illustrates only the volume at Moose. Overall the volume observed at the Moose end was slightly higher, but otherwise similar to that observed at the Granite Canyon entrance station.

The data in Table 2-2 and Table 2-3 was further used to determine the average monthly arrival rates and service rates. Table 2-4 illustrates the results of averaging the peak-hour arrival averages as well as the vehicle headways at Granite Canyon and only considering the Moose end monthly average arrivals. These results can be considered as the arrival rate and service rate when the system is experiencing the most substantial amount of arrivals in a given month.

Table 2-2 Arrival Rate, Headway and Service Rate Summary for Granite Canyon

Entrance Station

Date	Avg Day Arrivals (veh/hr)	Peak Hour	Peak Hour Arrivals	Avg Headway at Peak Hour/ Service Rate (veh/sec)
8/4/2013	82.27	10:45 AM - 11:45 AM	138	0:00:26
8/5/2013	80.18	9:30 AM - 10:30 AM	143	0:00:25
8/24/2013	64.92	10:00 AM - 11:00 AM	128	0:00:27
6/14/2014	48.06	10:45 AM - 11:45 AM	90	0:00:40
6/15/2014	62.35	10:15 AM - 11:15 AM	124	0:00:29
6/16/2014	46.00	9:15 AM - 10:15 AM	111	0:00:33
6/26/2014	55.63	10:30 AM - 11:30 AM	90	0:00:41
6/27/2014	55.35	9:45 AM - 10:45 AM	112	0:00:31
6/28/2014	63.49	10:00 AM - 11:00 AM	118	0:00:30
7/10/2014	64.73	8:45 AM - 9:45 AM	103	0:00:35
7/11/2014	64.39	8:45 AM - 9:45 AM	109	0:00:33
7/12/2014	68.49	9:30 AM - 10:30 AM	131	0:00:27
8/8/2014	73.18	9:45 AM - 10:45 AM	140	0:00:26
8/9/2014	66.35	8:45 AM - 9:45 AM	110	0:00:33
8/10/2014	76.22	9:30 AM - 10:30 AM	137	0:00:25
9/6/2014	52.82	10:15 AM - 11:15 AM	94	0:00:38
9/7/2014	57.65	9:00 AM - 10:00 AM	101	0:00:35
9/8/2014	47.61	9:30 AM - 10:30 AM	99	0:00:36
10/10/2014	21.24	10:30 AM - 11:30 AM	45	0:01:19
10/11/2014	23.76	9:45 AM - 10:45 AM	49	0:01:14
10/12/2014	15.55	9:45 AM - 10:45 AM	26	0:02:12

Table 2-3 Arrival Rate Summary for Proposed Moose Entrance Station

Date	Avg Day λ (veh/hr)	Peak Hour	Peak Hour Arrivals
8/4/2013	87.00	3:15 PM - 4:15 PM	151
8/5/2013	79.47	2:45 PM - 3:00 PM	127
8/24/2013	77.08	3:15 PM - 4:15 PM	127
6/14/2014	55.43	2:15 PM - 3:15 PM	93
6/15/2014	62.31	5:00 PM - 6:00 PM	100
6/16/2014	53.80	3:00 PM - 4:00 PM	87
6/26/2014	61.61	2:15 PM - 3:15 PM	118
6/27/2014	52.55	1:00 PM - 2:00 PM	83
6/28/2014	77.55	3:30 AM - 4:30 PM	131
7/10/2014	63.98	3:00 PM - 4:00 PM	92
7/11/2014	68.71	3:30 AM - 4:30 PM	115
7/12/2014	70.35	4:00 PM - 5:00 PM	106
8/8/2014	78.10	2:15 PM - 3:15 PM	122
8/9/2014	75.96	4:00 PM - 5:00 PM	142
8/10/2014	85.51	4:00 PM - 5:00 PM	139
9/6/2014	62.45	3:45 AM - 4:45 PM	109
9/7/2014	71.53	4:45 AM - 5:45 PM	91
9/8/2014	60.08	4:00 PM - 5:00 PM	90
10/10/2014	26.10	3:45 AM - 4:45 PM	46
10/11/2014	30.14	3:15 PM - 4:15 PM	56
10/12/2014	20.06	3:45 AM - 4:45 PM	40

Table 2-4 Monthly Arrival Rate, Headway and Service Rate Summary

Month	Monthly Peak Hour Avg		
	Avg Headway at Peak Hour/ Service Rate μ	Granite Canyon	Moose
Aug-13	0:00:26	136.33	135.00
Jun-14	0:00:31	107.50	102.00
Jul-14	0:00:32	114.33	104.33
Aug-14	0:00:34	129.00	134.33
Sep-14	0:00:34	98.00	96.67
Oct-14	0:00:35	40.00	47.33

The month of August is denoted as the month which saw the highest arrival rate, as well as the month which can be more confidently referenced to assume an adequate service rate. The peak hour arrival rates can be referred to as 137 and 129 vehicles per hour the for the Granite

Canyon entrance, 135 vehicles per hour for the Moose end and service rates ranging from 25 seconds to 35 seconds respectively.

2.8 Analysis and Results

Little’s Law was implemented to various scenarios in the analysis to observe the variance in the results. For conditions at the Granite Canyon entrance, an 83 vehicle per hour arrival rate was utilized since it was the most substantial daily arrival rate observed, thus making it the conservative choice. Service rate values were obtained by referencing the headways. Thus, a reasonable range of service rate was determined to be between 25 seconds to 35 seconds. Therefore, an arrival rate λ of 83 vehicles per hour was utilized with a service rate μ ranging from 25 seconds to 35 seconds. Table 2-5 illustrates the implementation of Little’s formula over the stated parameters. Figure 2-6 illustrates the probability of having 20 vehicles in the system under these circumstances.

Table 2-5 Results of Little’s Formula with $\lambda = 83$ veh/hr and $\mu = 25 - 35$ sec

Arrival Rate λ (veh/hr)	Service Rate μ (sec)	Traffic Intensity ρ	Facility Utilization %	Average					
				Length of System Ls (veh)	Length of Queue Lq (veh)	Waiting Time in System Ws (sec)/(min)		Waiting Time in Queue Wq (sec)/(min)	
83	25	0.58	58	1.36	0.78	59	0.98	34	0.57
	26	0.60	60	1.50	0.90	65	1.08	39	0.65
	27	0.62	62	1.65	1.03	72	1.19	45	0.74
	28	0.65	65	1.82	1.18	79	1.32	51	0.85
	29	0.67	67	2.02	1.35	88	1.46	59	0.98
	30	0.69	69	2.24	1.55	97	1.62	67	1.12
	31	0.71	71	2.51	1.79	109	1.81	78	1.29
	32	0.74	74	2.81	2.08	122	2.03	90	1.50
	33	0.76	76	3.18	2.42	138	2.30	105	1.75
	34	0.78	78	3.63	2.84	157	2.62	123	2.06
	35	0.81	81	4.18	3.37	181	3.02	146	2.44

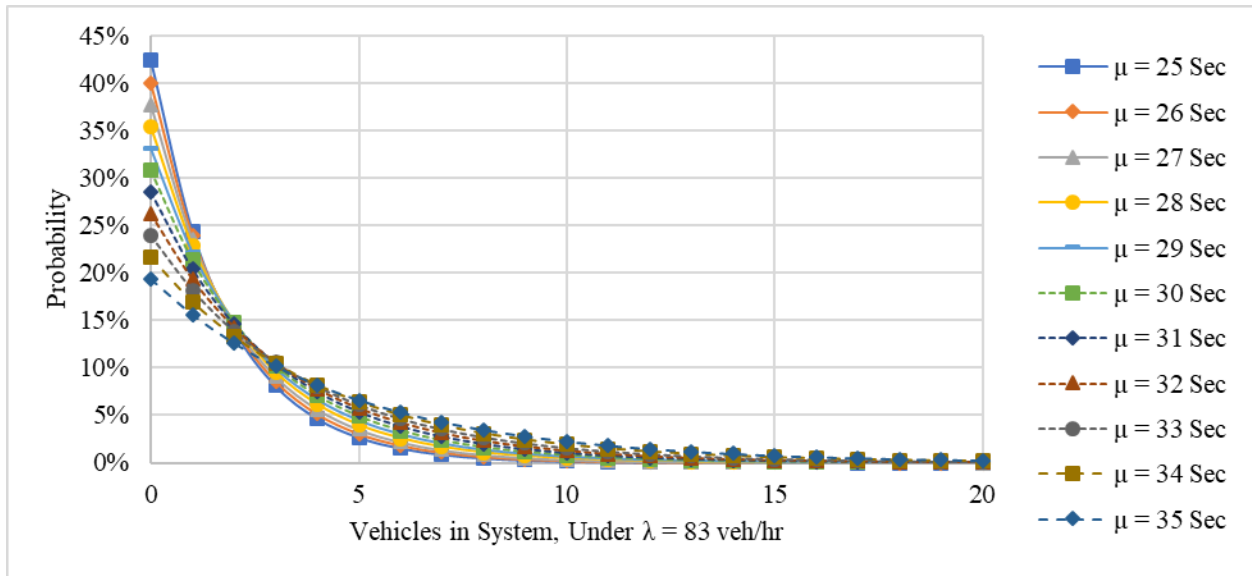


Figure 2-6 Probabilities of 0 – 20 Vehicles in the System with $\lambda = 83$ veh/hr and $\mu = 25 – 35$ sec.

The results show that the expected number of vehicles in the queue at a 25-second service rate is 0.78 and increases to 3.37 vehicles when the service rate is 35 seconds. Similarly, the average time a vehicle spent in the queue was approximated to range from 34 seconds to 2 minutes and 26 seconds, while the facility usage ranged from 58% to 81%. Figure 2-6 shows that the probability of having zero vehicles in the system decreases by approximately 20% when the service rate is increased by ten seconds.

Applying the same principles, the Moose end queueing measures of performance were estimated using Little’s Law. Therefore, an arrival rate λ of 87 vehicles per hour was utilized with a service rate μ ranging from 25 seconds to 35 seconds. Table 2-6 illustrates the application of Little’s formula over the stated parameters. Figure 2-7 illustrates the probability of having 20 vehicles in the system under these circumstances.

Table 2-6 Results of Little's Formula with $\lambda = 87$ veh/hr and $\mu = 25 - 35$ sec

Arrival Rate λ (veh/hr)	Service Rate μ (sec)	Traffic Intensity ρ	Facility Utilization %	Average					
				Length of System L_s (veh)	Length of Queue L_q (veh)	Waiting Time in System W_s (sec)/(min)		Waiting Time in Queue W_q (sec)/(min)	
87	25	0.60	60	1.53	0.92	59	0.98	38	0.64
	26	0.63	63	1.69	1.06	65	1.08	44	0.73
	27	0.65	65	1.88	1.23	72	1.19	51	0.84
	28	0.68	68	2.09	1.42	79	1.32	59	0.98
	29	0.70	70	2.34	1.64	88	1.46	68	1.13
	30	0.73	73	2.64	1.91	97	1.62	79	1.32
	31	0.75	75	2.99	2.24	109	1.81	93	1.54
	32	0.77	77	3.41	2.64	122	2.03	109	1.82
	33	0.80	80	3.94	3.14	138	2.30	130	2.17
	34	0.82	82	4.61	3.79	157	2.62	157	2.61
	35	0.85	85	5.49	4.64	181	3.02	192	3.20

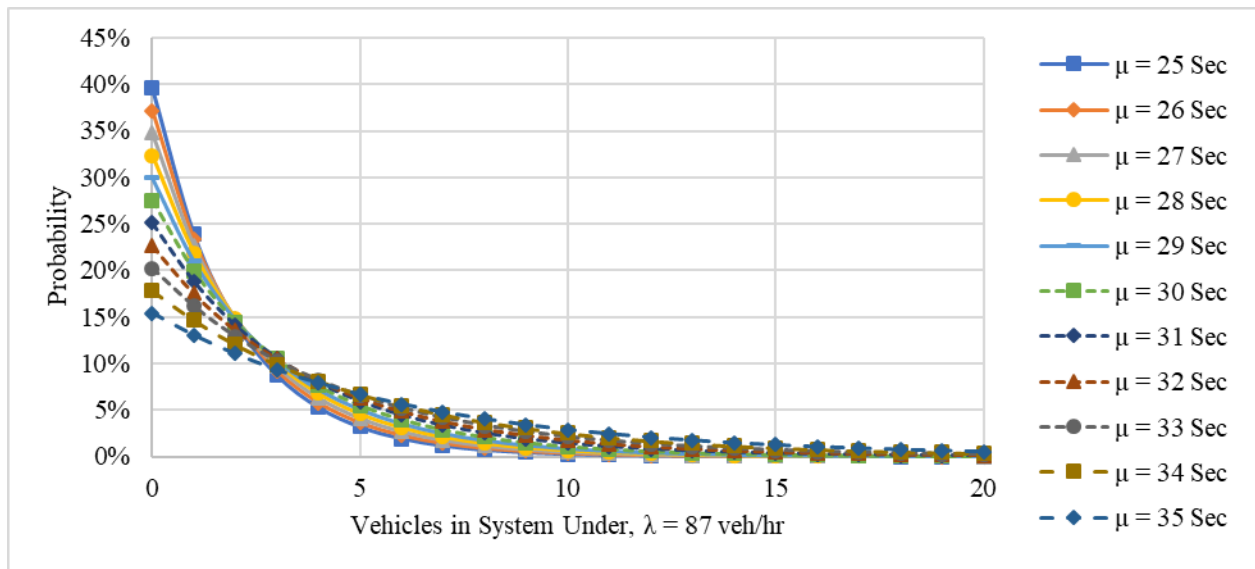


Figure 2-7 Probabilities of 0 – 20 Vehicles in the System with $\lambda = 87$ veh/hr and $\mu = 25 - 35$ sec

The results show that the expected number of vehicles in the queue at a 25-second service rate is 0.92 and increases to 4.64 vehicles when the service rate is 35 seconds. Similarly, the average time a vehicle spent in the queue was approximated to range from 38 seconds to 3

minutes and 12 seconds, while the facility usage ranged from 60% to 85%. Figure 2-7 shows that the probability of having zero vehicles in the system decreases by approximately 25% when the service rate is increased by ten seconds.

Furthermore, the additional parameters considered were those where the arrival rates were significant. Little's Law was once again utilized to measure the performance at higher arrival rates and service times. For these iterations, the arrival rate of 129, 137 and 143 vehicles per hour for the Granite Canyon entrance and 135 and 151 vehicles per hour for the Moose end proposed entrance were tested with service rates varying between 26 and 35 seconds. These values were considered by the results shown in Table 2-3 and Table 2-4 and are evaluating the longer peak hours observed in the collected data. Although the results are high for these scenarios, it provides an idea of how the performance measures are sensitive to the service and arrival rates in Little's Law. Additionally, cases, where the service rate could not keep up with the demand, resulted in unstable queueing, in which Little's Law is no longer useful, and additional measures must be taken to address the queue. Table 2-7 and Table 2-8 illustrates the application of Little's Law to the Granite Canyon entrance station and the proposed Moose end entrance station, respectively.

Table 2-7 Results of Little’s Formula with $\lambda = 129, 137, 143$ veh/hr and $\mu = 26-35$ sec for the Granite Canyon Entrance Station

Arrival Rate λ (veh/hr)	Service Rate μ (sec)	Traffic Intensity ρ	Facility Utilization %	Average					
				Length of System L_s (veh)	Length of Queue L_q (veh)	Waiting Time in System W_s (sec)/(min)		Waiting Time in Queue W_q (sec)/(min)	
129	26.0	0.93	93	13.63	12.70	380	6.34	354	5.91
	27.8	1.00	100	237.57	236.57	6630	110.50	6602	110.03
	35.0	1.25	125	Unstable					
137	26.0	0.99	99	93.74	92.75	2463	41.05	2437	40.62
	26.2	1.00	100	338.62	337.63	26	0.44	8872	147.87
	35.0	1.33	133	Unstable					
143	26.0	1.03	103	298.90	298.00	7800	130.00	7774	129.57
	35.0	1.39	139	Unstable					

Table 2-8 Results of Little’s Formula with $\lambda = 135$ and 151 veh/hr and $\mu = 26-35$ sec for the Proposed Moose Entrance

Arrival Rate λ (veh/hr)	Service Rate μ (sec)	Traffic Intensity ρ	Facility Utilization %	Average					
				Length of System L_s (veh)	Length of Queue L_q (veh)	Waiting Time in System W_s (sec)/(min)		Waiting Time in Queue W_q (sec)/(min)	
135	26.0	0.98	98	39.00	38.02	1040	17.33	1014	16.90
	26.6	1.00	100	399.00	398.00	10640	177.33	10613	176.89
	35.0	1.31	131	Unstable					
151	26.0	1.09	109	Unstable					
	26.2	1.10	110	Unstable					
	35.0	1.47	147	Unstable					

Although the results from Table 2-7 and Table 2-8 show unstable results, the values utilized were for the highest observed volumes and would likely not be consistent for longer than an hour. However, they do illustrate how small changes in service time can have a significant impact on measures of performance.

The last analysis method utilized was a simulation. The simulation parameters used were similar to those used in the Little’s formula analysis. A total of 20 simulations with 160 vehicles was conducted for each case. The number of simulations was determined based on having a

sample size sufficient enough to capture possible variances. As described by Ritter et al. the number of simulations required can vary for stochastic simulations (*Rothrock and Narayanan 2011*). The 160 vehicles considered were to make sure that at least one hour was simulated for each case. The facility utilization, in this case, was determined as the summation of the time the facility was attending to a visitor. The idle time was then determined by subtracting the facility time over the total simulation time. Table 2-9 and Table 2-10 illustrate the average results of each simulation scenario in the Granite Canyon entrance station and the proposed Moose entrance station, respectively

Table 2-9 Average Results of 160 Vehicle Simulation Under Varying Arrival and Service Rates at the Granite Canyon Entrance Station

Arrival Rate λ (veh/hr)	Service Rate μ (sec)	Average								
		% Facility Utilization	% Idle	Queue Length, Lq (veh)	System Length, Ls (veh)	Waiting Time in Queue Wq (sec)/(min)		Waiting Time in System Ws (sec)/(min)		Total Simulation Time (min)
83	25	57	43	0.80	1.37	35	0.58	60	1.00	106.53
	35	78	22	2.80	3.58	122	2.03	156	2.60	105.99
129	25	85	15	3.91	4.75	113	1.88	137	2.29	71.24
	35	99	1	20.22	21.21	732	12.21	768	12.79	86.56
137	25	87	13	5.46	6.34	150	2.49	174	2.90	68.02
	35	99	1	23.52	24.51	844	14.07	880	14.66	85.95
143	25	92	8	7.70	8.61	214	3.56	239	3.98	66.91

Table 2-10 Average Results of 160 Vehicle Simulation Under Varying Arrival and Service Rates at the Proposed Moose Entrance Station

Arrival Rate λ (veh/hr)	Service Rate μ (sec)	Average								
		% Facility Utilization	% Idle	Queue Length, Lq (veh)	System Length, Ls (veh)	Waiting Time in Queue Wq (sec)/(min)		Waiting Time in System Ws (sec)/(min)		Total Simulation Time (min)
87	25	60	40	1.00	1.60	40	0.67	65	1.08	99.57
	35	83	17	4.46	5.29	192	3.20	228	3.80	106.18
135	25	90	10	5.14	6.04	143	2.39	168	2.80	66.88
	35	98	2	21.45	22.43	774	12.90	809	13.49	87.54
151	25	94	6	10.52	11.46	287	4.78	312	5.20	65.91

The results obtained from the simulation showed values comparable to those obtained by Little’s formula when the arrival and service rates were low. However, it appeared that the simulation results for the higher arrival and service rates which were determined to be unstable under Little’s Law were more reasonable in terms of queue length and queue waiting time per vehicle. This could be explained by the traffic intensity value ρ being high, or closer to one when using Little’s Law.

2.9 Discussion of Results

From referencing both Little’s Law and the simulation results above, it can be observed that an average arrival rate of 83 - 87 vehicles per hour with a varying service rate of 25 seconds to 35 seconds can adequately handle the arriving visitors at the Granite Canyon entrance and a Moose entrance station. Under these conditions, the maximum facility utilization can be anticipated to be at 85% with a maximum average queue length of 3.4 to 4.3 vehicles and a maximum average queue waiting time of 2 minutes 15 seconds to 2 minutes 59 seconds.

The conditions which were determined to see the most substantial arrival rates of 143 and 151 vehicles per hour were found to be unstable when utilizing Little's Law. However, simulation results determined that under these parameters and a relatively effective service rate of 25 seconds, the facility utilization is between 92% - 94%, with a maximum average queue length of 10.52 vehicles and a 4 minute and 48-second average queue waiting time. For comparison, Upchurch reported a wait time ranging from 10 – 22 minutes at Zion National Park (*Upchurch 2015*). Although the estimated wait time is lower than what has been observed at other National Parks, consideration must be made to visitor perception. In most systems, waiting time is a factor that is trying to be minimized in order to increase customer/visitor satisfaction. However, in a National Park setting, wait time minimization may not be as critical due to visitors likely participating in leisure activities.

The determined service rate of 25 seconds seems appropriate for the Granite Canyon entrance, in comparison to the 32 seconds service at Arches National Park entrance station and a service rate of 37 seconds for Grand Canyon National Park's south entrance (*Upchurch 2006*). The capacity at the Granite Canyon entrance was estimated to be 144 vehicles per hour averaging a service rate of 25 seconds. Compared to other entrance stations, the capacity for Arches National Park, Grand Canyon National Park, and Zion National Park were determined to be 112 vehicles per hour, 97 vehicles per hour and 194 vehicles per hour, respectively (*Upchurch 2006; Upchurch 2015*). An essential distinction between the entrance station evaluated in GRTE and those evaluated by Upchurch is in their anticipated demand as those evaluated by Upchurch can be considered as the primary entrances to their respective National Parks.

Lastly, the results provide an estimated vehicle queue length which could be converted into a distance when assuming a vehicle length and multiplying these two variables. When

considering the future policy of a Moose queuing station, it is essential to consider how the queue length will affect system performance but also safety concerns. If the entrance station is too close to the intersection, the queue may spill back to the MWC and Teton Park road intersection resulting in poor traffic conditions, possible negative visitor experiences and safety concerns from approaching upstream traffic.

A study by Mokkaapati and Hawkins focused on guidelines for minimum signal sight distance considers a distance of 15.2 meters (50 ft) for two vehicles in the queue (*Mokkaapati and Hawkins 2007*). The ITE Traffic Engineering Handbook lists a passenger vehicle and single-unit truck with a length of 5.8 meters (19 ft) and 9.1 meters (30 ft) respectively (*Pande et al. 2015*). With passenger vehicle length information, a spacing of about 3.7 meters (12 ft) can be presumed. However, for the MWC, consideration must be taken to account the variation in vehicle type and spacing when queuing. Therefore, considering a 5-vehicle queue estimated under the 87 vehicles per hour arrival rate at the Moose end and assuming all passenger vehicles with 3.7 meters (12 ft) spacing between queued vehicles, an approximate 43.8 meter (143 ft) distance would be expected. However, if the same conditions apply, and we consider all single-unit trucks instead of all passenger vehicles, the distance increases to 60.3 meters (198 ft). Thus, estimating a distance can vary considerably under different assumptions, and a realistic scenario has mixed vehicles and mixed spacings in play. A conservative assumption may be to presume a 5-vehicle queue, with four passenger vehicles and one single-unit truck and 3.7 meters (12 ft) spacing. The technical report of the suite of data collected for the development of the Moose-Wilson Corridor Comprehensive Management Plan reported small observations of trucks and vans (*Monz et al. 2014*). Thus, under these considerations, a minimum distance recommendation

for the Moose end queueing station would be approximately 47.1 meters (154 ft) downstream from the Teton Park Road intersection.

It is important to mention that the queuing distance estimation is for current prevailing conditions with a one-lane entry. Therefore, the results presented would be valid to Final Plan/EIS's strategy when arriving vehicles are not affected by the MWC 200 vehicles at a time capacity constraint. Consequently, the Final Plan/EIS's strategy to implement the addition of lanes at both the Granite Canyon entrance and the Moose queueing station will serve as a positive feature in maintaining capacity and preventing the spill back to Teton Park Road (*National Park Service 2016c*).

2.10 Policy Implications

The policy implications as they relate to this case study are twofold. First, the current assessment of the Granite Canyon entrance has provided a base level of existing conditions for queuing operations. The procedure presented in this study provides an approach which is repeatable by GRTE when the Moose entrance station is fully operational. Policy decisions made by the GRTE administration related to current operations may be to set thresholds on service times, capacity, facility utilization or queue lengths. By referencing this case study, a balance between park preservation, visitor satisfaction, and GRTE staff could be further explored by GRTE. As it relates to findings in this study, service time changes by considering additional servers should be considered by GRTE when arrival rates are expected to exceed 100 vehicles per hour and similarly, when service time is frequently exceeding 35 seconds. Thus, a conservative recommendation would make the capacity of 103 vehicles per hour a recommended threshold for the Granite Canyon and Moose end entrance stations.

Secondly, the use of queuing theory methodology was further utilized to anticipate queueing levels at a new site within GRTE. In this case study, the proposed Moose entrance station was evaluated by utilizing collected data and assumptions of similar service time to the Granite entrance station. The knowledge gained from the queueing operation assessment provides policy decision-makers with crucial information for useful planning data for future operations as well as initial thresholds on service times, facility utilization or queue lengths. As it relates to findings in this study, the proposition of a new entrance station would need to consider the upstream effects of arriving vehicles and their respective queues. It is recommended based on initial assumptions that the distance of 47.1 meters (154 ft) is a conservative minimum distance for GRTE policy and decision makers to take into consideration.

Overall the policy implications that are queuing brings to GRTE must be assessed with careful consideration. Entrance stations are commonly implemented to control access, and their function can influence preservation strategies by how many visitors enter the park and similarly visitor satisfaction by setting thresholds and goals that minimize delay during the entering processes.

2.11 Conclusions

In conclusion, it was determined that the consideration of queueing theory methodologies could provide useful information when considering policy changes. Overall, vehicle arrival rate data was collected from which queueing length and waiting time were estimated. Additionally, results from the queueing analysis were further extended to the estimation of a safe distance recommendation for a proposed entrance station. This information & procedure can be used to determine and evaluate current operations as well as setting thresholds to a desired level of

operation in future policy decisions. The procedure used in this study applies to any queuing setting in a National Park or protected area, where policy changes are being proposed or considered.

The setting and application of queueing theory methodology for this study took place in the MWC in the GRTE. Specifically, it was determined that the Granite Canyon entrance could be evaluated as an *M/M/1* first come first served (FCFS) queue. From data collected for the years of 2013 and 2014, the month of August is the month in which highest vehicle arrivals were observed at the Granite Canyon entrance. The capacity for the Granite Canyon entrance was determined to be 144 vehicles per hour. The average daily arrival rate of 83 vehicles per hour was determined to be a conservative value for the Granite Canyon entrance. Similarly, a service rate of 25-30 seconds can be considered an adequate value for the observed arrival rate. Under this condition, the anticipated facility utilization can be expected to be 81%, with an idle expectancy of 19%.

When considering the proposed queueing station at the Moose end of the park, the evaluation was also approached as an *M/M/1* first come first served (FCFS) queue. The average daily arrival rate of 87 vehicles per hour was determined to be a conservative value for the proposed Moose entrance. Similarly, a service rate of 25-30 seconds can be considered an adequate value for the observed arrival rate. Under this condition, the anticipated facility utilization can be expected to be 85%, with an idle expectancy of 15%.

Some of the more extreme parameters considered were those in which the vehicle arrivals were higher than 100 vehicles per hour, and the service rate was estimated at 35 seconds. These were determined to be unstable under Little's Law. However, the simulation results provided

high estimates of queue length and queue waiting time with facility utilization values higher than 90%.

What these results can translate into is that currently, operations at the Granite Canyon entrance station are adequate. Furthermore, a Moose queuing station can expect similar arrival rates as the Granite Canyon entrance. However, the peak hours would likely shift between high AM arrivals at the Granite Canyon entrance and high PM arrivals at the Moose queuing station. Lastly, careful consideration of the queue lengths and distance estimates must be considered when locating the Moose queuing station, as possible queue spill back into the MWC and Teton Park intersection could occur. A conservative distance downstream from the Teton Park Road intersection was estimated to approximately 47.1 meters (154 ft). The current Final Plan/EIS's proposal to include more than one lane should mitigate the issue of spillback.

2.12 Applying Findings into an Agent-Based Model

Applying the methodology discussed in this chapter to an ABM requires the consideration of two main aspects. One is the arrival rate of vehicles arriving at the entrance gate and the other is the service time at the gate before they can proceed. The arrival rate of vehicles can be modeled by the mathematical equation illustrated in Eq. 2.9. By utilizing the ABM's platform capabilities, a random number generator can be generated and be used to solve for the interarrival time that a vehicle is introduced to the ABM and thus representing the vehicle arrival rates. Every interarrival time can be stored in a list and be coded to release a vehicle into the ABM once that specific time is reached. In Eq. 2.9 the *lambda* is the user specified arrival rate parameter in units of seconds/vehicle. Thus, giving the user flexibility into testing observing various arrival rates.

The same process can be implemented in terms of service time. However, modeling such an event in an ABM requires the consideration of a conditional constraint to the agent or environment. For example, an agent may be instructed to stop if the cell in front of it is the color red and can proceed if the cell is changed to the color green. Similarly, interservice times can be calculated based on the user specified λ arrival rate.

Therefore, by incorporating these two rules and instructing the agents(vehicles) that they are not allowed to pass any agent(vehicle) in front of them. Queueing system levels and anticipated queue lengths can be modeled in an ABM and thus generate synthetic data of various combinations of vehicle arrival rates and service times.

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3 CHAPTER 3: Evaluation of Vehicle Parking Queueing in a National Park: A Case Study of the Laurence S. Rockefeller Preserve in Grand Teton National Park

This chapter is adapted from Fuentes, A., Heaslip, K., D'Antonio, A. Khalilikhah, M., Soltani-Sobh, A., (2017) Evaluation of Vehicle Parking Queueing in a National Park: A Case Study of the Laurence S. Rockefeller Preserve in Grand Teton National Park. Transportation Research Record, 2654, 1-10.

3.1 Introduction

Grand Teton National Park (GRTE) is a popular destination for visitors seeking a family vacation, outdoor recreation, and the possibility of wildlife sightings. The park attractions available to visitors influence how visitors plan their trip and which park routes will be used to reach their destination. In order to take full advantage of their visit to GRTE, visitors are likely to take more extended periods either at or during their commute to their final destination. The amount of time visitors spend at a location could be directly associated with the types of activities offered and similarly, the type of visitor (local visitor, out of state visitor, a park employee).

Arguably the more popular attractions which have facilities are located near each other. These locations include the Laurence S. Rockefeller Preserve (LSR), the GRTE Headquarters, the Craig Thomas Discovery and Visitor Center, and Teton Village (which is located just southwest of the Granite Canyon entrance to GRTE). The LSR is located within the park

boundaries northeast of Teton Village and southwest of the Park Headquarters and Visitor Center. The GRTE Headquarters and the Craig Thomas Discovery and Visitor Center are located near the end of the Moose-Wilson Road corridor (MWC) by intersecting with Teton Park Road in the community of Moose. Figure 3-1 presents a map of the previously discussed area where these attractions are located, and a zoomed given the LSR. These attractions all provide a parking area for visitor vehicles and can be accessed either directly through or relatively quickly by the MWC. The LSR is located roughly halfway between Teton Village and the Moose community. The LSR is a unique attraction due to providing both activities at the facility and having various hiking trails nearby, as well as its proximity to Phelps Lake which offers fishing activities. This combination might influence visitors to utilize the parking area provided for long periods, leading to concern of overcapacity, queueing and possible visitor loss if visitors arrive at a more significant rate than visitors who are leaving and are unable to find parking. There are often delays, sometimes significant, that occur when people are trying to access the LSR with their vehicles. During peak periods the National Park Service (NPS) deploys one or more personnel to the parking area to assist visitors and manage the parking as effectively as possible.

The purpose of this study is to provide GRTE, as well as other national parks, a reference in evaluating the measures of performance in other parking systems. More specifically, it can be used as a guide to determine current use levels and track how these levels change throughout the season, or years. If high use levels are found frequent, then improvements such as expansion or timed parking can be implemented, as needed. This will be accomplished by focusing on evaluating the queue characteristics at the LSR attraction.

3.2 Literature Review

There is limited literature on parking in national parks. The research team studied previous research by Upchurch which investigated the visitor experience at Zion's National Park in Utah by assessing the shuttle service and parking areas. Parking areas for visitors were monitored in order to assess time when capacity is reached, and overflow parking is used on high visitation days (*Upchurch 2015*). Some variation from Upchurch's investigation to those in this study is the geography of the parking area. The parking area studied by Upchurch saw a large volume of vehicles because it is considered to be the central parking for Zion's National Park. Also, shuttle services to the rest of the park are offered at this location. The LSR parking is a smaller area that is visited due to particular interest from visitors and thus does not see as high visitor volumes. Although more studies relating specifically to a national park parking area have not been conducted, this study, along with Upchurch's work, open the door to various analysis methods.

3.3 Study Area

The LSR is accessed by making a southbound movement at the intersection of MWC and the LSR entrance road. Roughly, over a quarter of a mile south of the intersection lies the LSR parking area. Figure 3-1 illustrates an aerial image of this location. Furthermore, a representative image of the available parking is illustrated in Figure 3-2. There are 54 – 55 designated parking spaces (*Monz et al. 2014; Monz et al. 2015*) and parking in any other areas such as the shoulder of the access road are prohibited. If parking is observed in the shoulder, ticketing by park employees is enforced. Overall, the LSR parking area can be considered a system in which vehicles enter, park for some time, and depart.

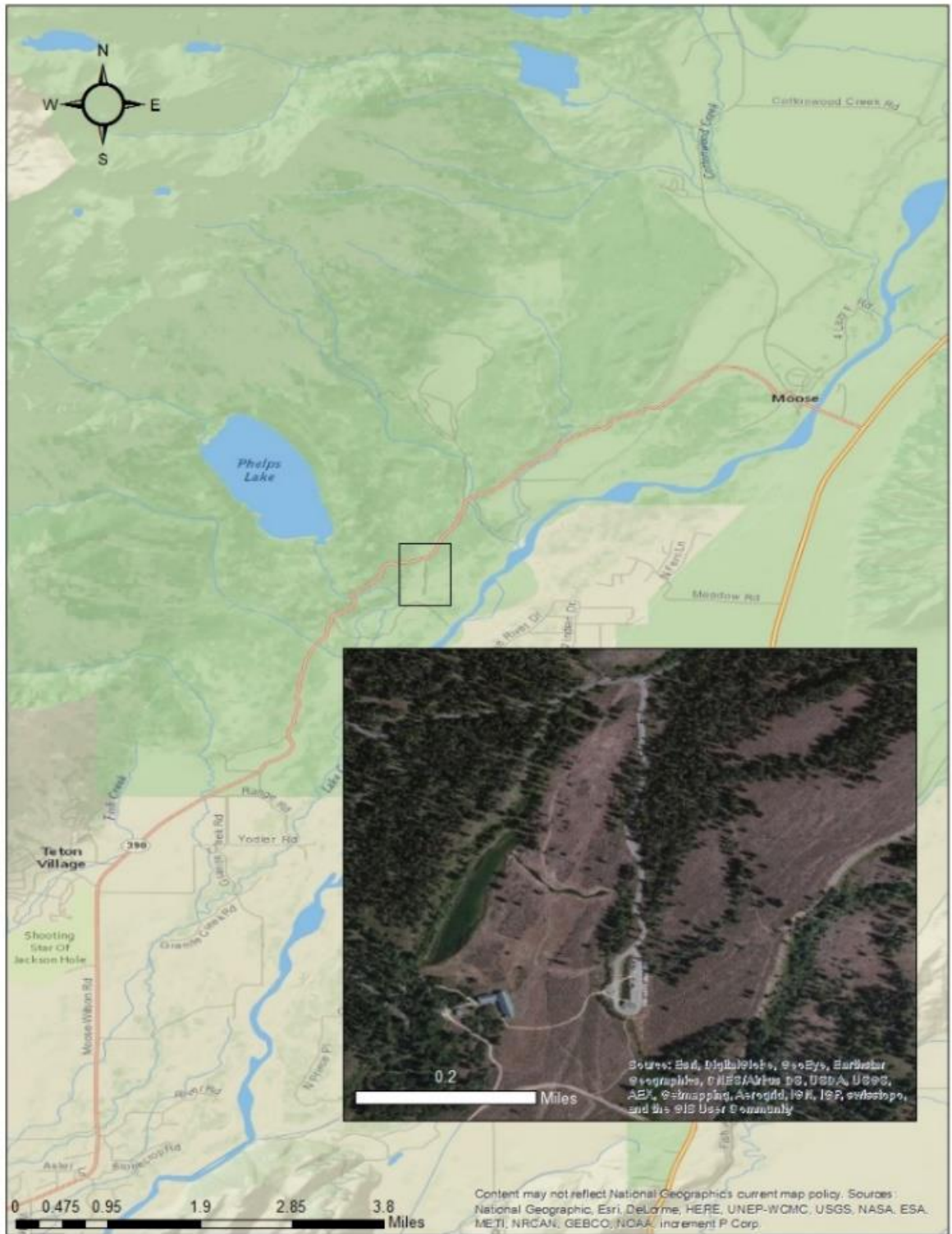


Figure 3-1 GRTE Attractions on the Moose-Wilson Corridor

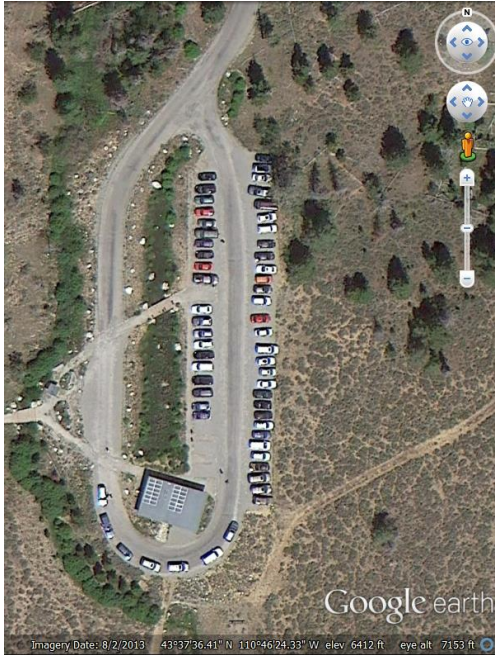


Figure 3-2 Google Earth Image Excerpt of LSR Parking

To define the LSR parking system in terms of queuing theory descriptions, the distinction of *approach/departure/number of servers* must be made. In the case of the LSR, the vehicle arrivals and departures are random. Thus the parking system can be assessed as a Poisson distribution denoted by the letter M ; the queuing discipline can be interpreted as service in random order (SIRO). The *number of servers* is considered the number of available parking spaces. Therefore, under the previously defined information, the LSR parking area can be considered as an $M/M/54$ system to remain conservative. However, from aerial observations, as can be seen in Figure 3-2, seven additional parking spaces on the south end of the loop could be considered as parking spaces. Thus, the LSR system could also be considered as an $M/M/61$. Further discussion on the consideration of the system as $M/M/54$ and $M/M/61$ is provided below.

3.4 Data Collection and Assumptions

The data utilized for this study was gathered from some different sources. Two key data were required to evaluate the queueing condition in LSR parking system. First, the total number of vehicles that arrive at the LSR and second, the average amount of time each vehicle spent parked at the LSR parking.

The method used to determine the arrival of vehicles was through the use of MioVision cameras. A camera captured the vehicle turning movement at the intersection of MWC and the entry road to the LSR. The average time that a vehicle spent parked at the LSR was determined through assessing GPS tracks. This data was obtained by visitors who agreed to participate in the study and were given a GPS device upon entry to MWC (either at the south Granite Canyon entrance station or the intersection of MWC and Teton Park Road in the north). By obtaining the visitor tracks with time stamps, the amount of time a vehicle was spent parked at the LSR was able to be determined.

Both sets of data were collected during the summer and fall seasons of 2013 and 2014. The intersection movement count focused on 13 hours from 7:00 AM – 8:00 PM in which data were collected on random days over a total period of eight months. During 2013, a total of 11 days were collected between July – September. During 2014, a total of 15 days were collected between June – October. Similarly, the GPS tracking of vehicles took place during 2013 from July – September for 23 days and during 2014 from June – October for 35 days. Each day of GPS tracking had a variable amount of data due to the collection from a stratified random sample, dependent on visitor participation and visitation levels.

There is uncertainty on whether every vehicle seen entering into the LSR system had the intentions of parking. For this reason, a fundamental assumption is made in order to be conservative. The assumption is that all observed vehicles turning into the LSR system would park and spend time at the LSR. Furthermore, from reference to Figure 2, it is assumed that the area large enough to fit the seven vehicles can be considered as a temporary parking area. The final assumption consists of assuming vehicles can use this parking if all available spaces are full as a “waiting area” until a parking space becomes available.

Both the *M/M/54* and *M/M/61* systems are considered simultaneously in this study by performing the calculations for an *M/M/61* system. The reasoning behind this decision lies in the ability to determine a queue length when considering temporary parking. If temporary parking is not considered, the queue length cannot be accurately estimated as the process would consider it as a visitor loss rather than estimating the queue length. Considering seven parking spaces is appropriate, as observations during the data collection process recorded a maximum of 6.4 vehicles waiting in the queue during August of 2014 (*Monz et al. 2014*).

3.5 Overview of Collected Data

The intersection movement count collected three vehicle movements: those traveling northeast towards the MWC and Teton Park Road intersection, southwest towards the Granite Canyon entrance, and southbound towards the LSR. The vehicle arrival rate into the system is provided in the following summaries of the southbound movements into the LSR. Figures 3-3 – 3-10 summarize the observed arrival rate for each month of data collection.

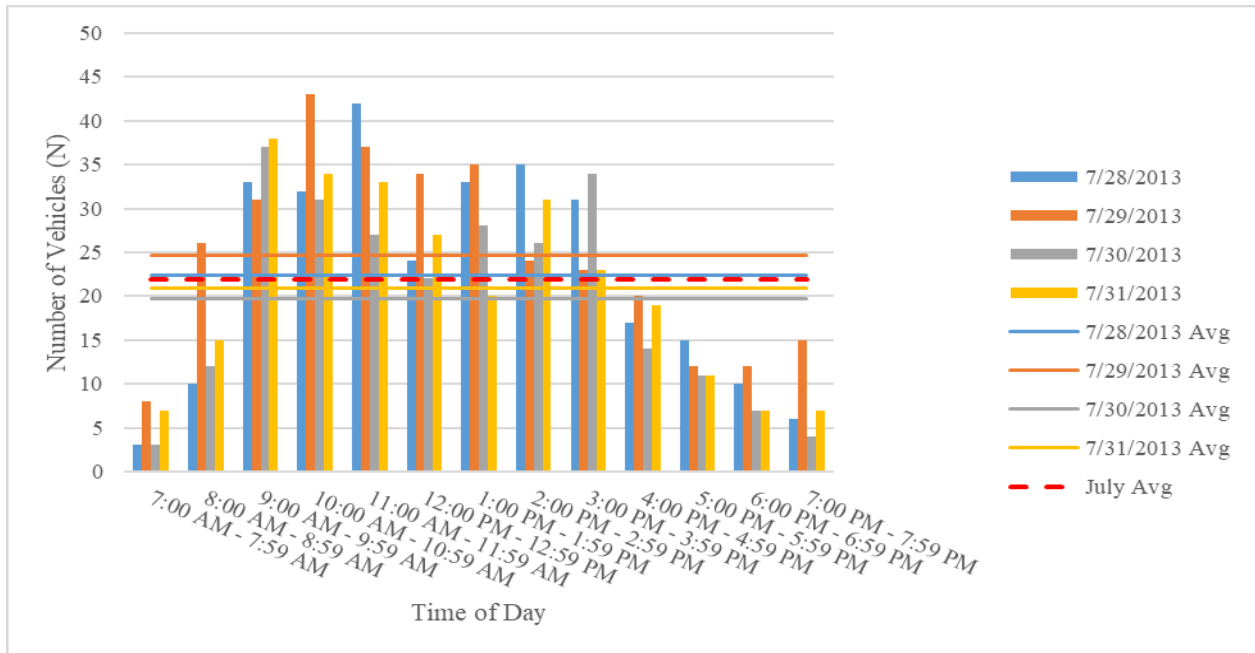


Figure 3-3 July 2013 LSR Vehicle Arrivals

The data collected in July 2013 consisted of four days of 13-hour observations. The dates of 7/28, 7/29, 7/30 and 7/31 correspond to Sunday, Monday, Tuesday and Wednesday respectively. The maximum peak hour was observed at 43 vehicles per hour from 10:00 AM – 10:59 AM on Monday 7/29, while the monthly average was determined to be 21.9 vehicles per hour.

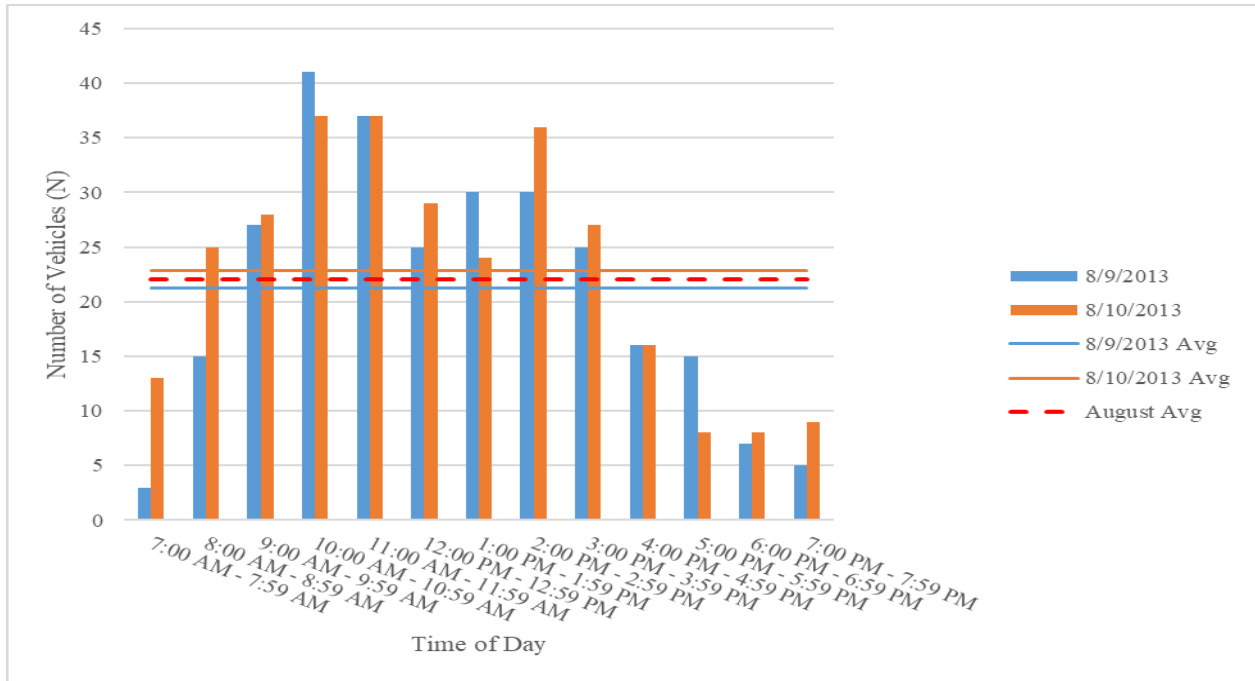


Figure 3-4 August 2013 LSR Vehicle Arrivals

The data collected in August 2013 consisted of two days of 13-hour observations. The dates of 8/9 and 8/10 correspond to Friday and Saturday respectively. The maximum peak hour was observed at 41 vehicles per hour from 10:00 AM – 10:59 AM on Friday 8/9, while the monthly average was determined to be 22.0 vehicles per hour.

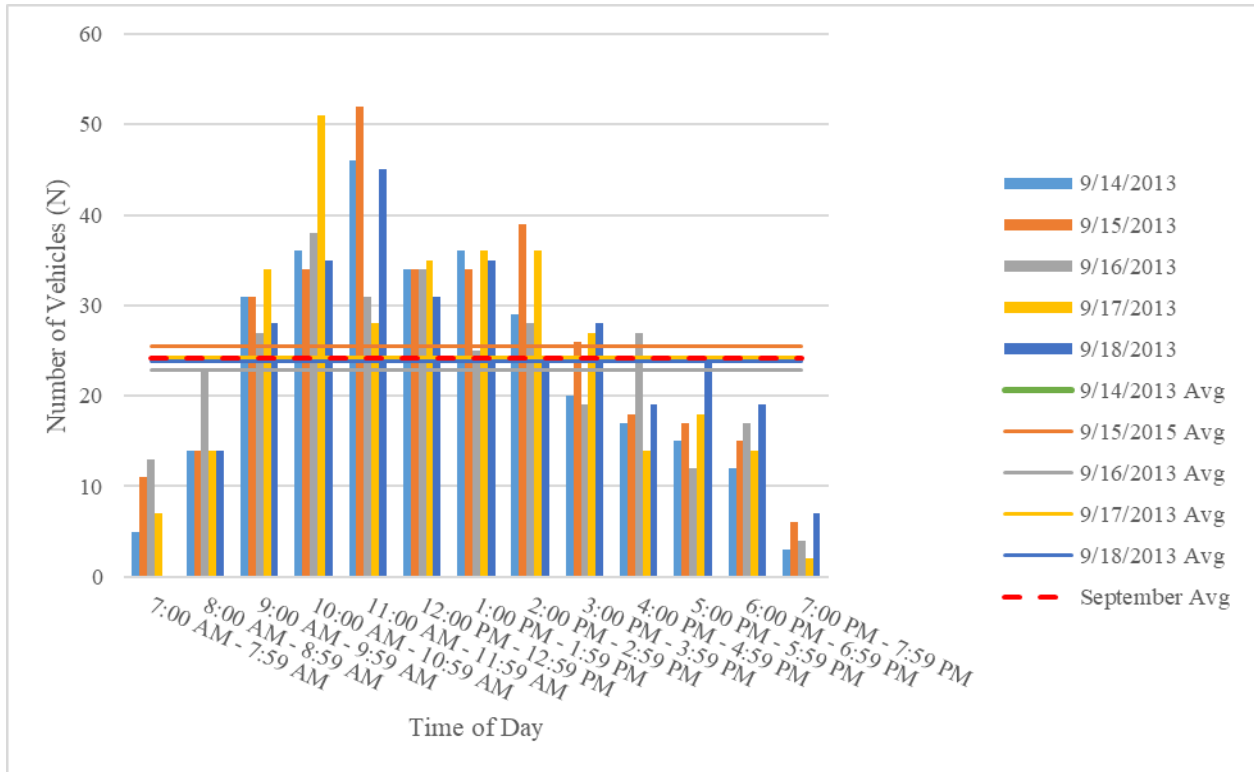


Figure 3-5 September 2013 LSR Vehicle Arrivals

The data collected in September 2013 consisted of five days of 13-hour observations. The dates of 9/14, 9/15, 9/16, 9/17 and 9/18 correspond to Saturday, Sunday, Monday, Tuesday and Wednesday respectively. The maximum peak hour was observed at 52 vehicles per hour from 11:00 AM – 11:59 AM on Sunday 9/15, while the monthly average was determined to be 24.1 vehicles per hour.

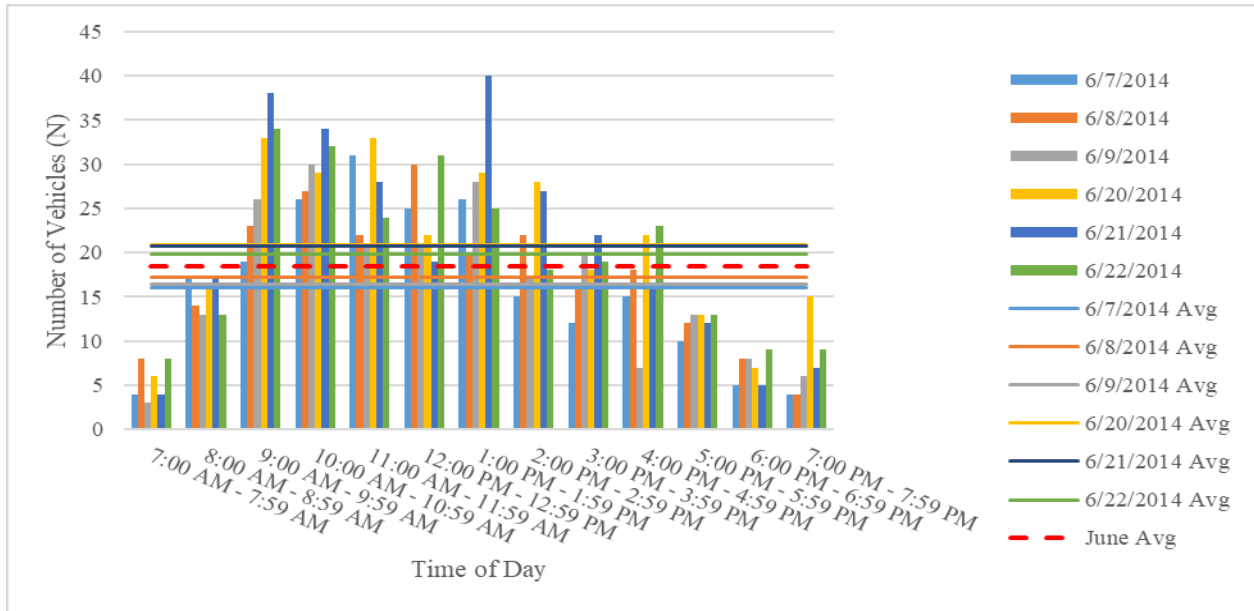


Figure 3-6 June 2014 LSR Vehicle Arrivals

The data collected in June 2014 consisted of six days of 13-hour observations. The dates of 6/7, 6/8, 6/9, 6/20, 6/21, and 6/22 correspond to Saturday, Sunday, Monday, Friday, Saturday and Sunday respectively. The maximum peak hour was observed at 40 vehicles per hour from 1:00 PM – 1:59 PM on Saturday 6/21, while the monthly average was determined to be 18.5 vehicles per hour.

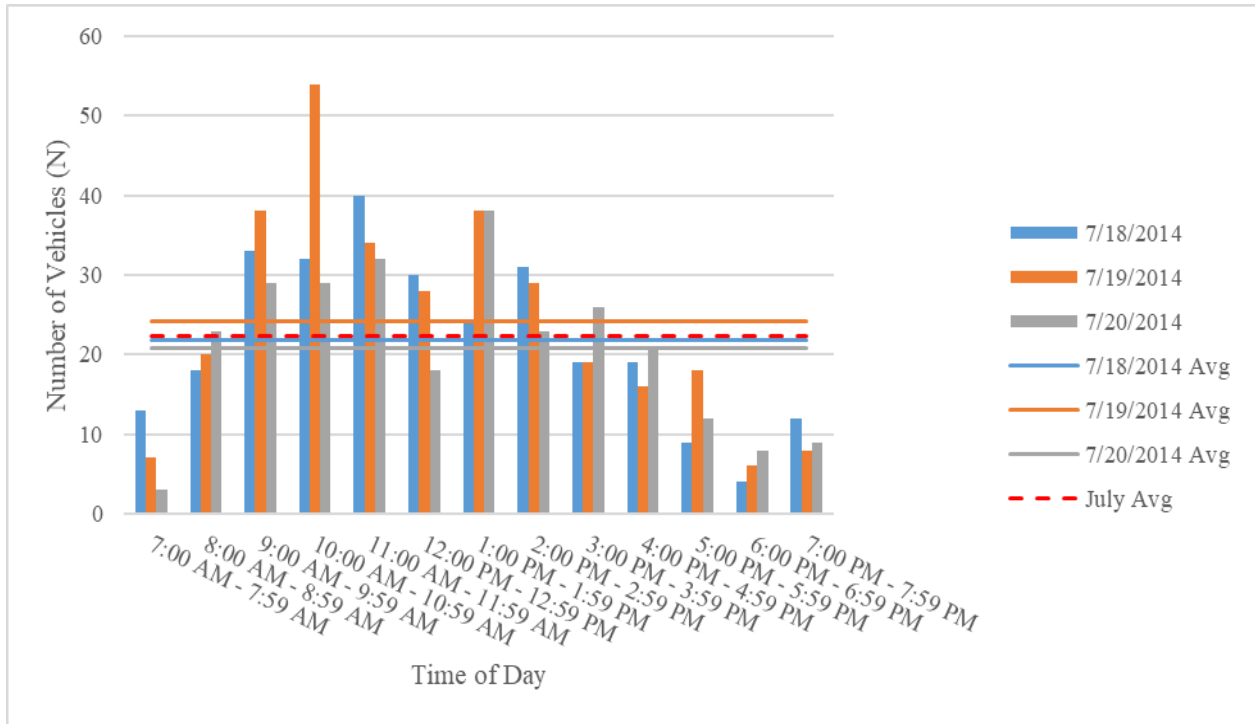


Figure 3-7 July 2014 LSR Vehicle Arrivals

The data collected in July 2014 consisted of three days of 13-hour observations. The dates of 7/18, 7/19 and 7/20 correspond to Friday, Saturday and Sunday respectively. The maximum peak hour was observed at 54 vehicles per hour from 10:00 AM – 10:59 AM on Saturday 7/19, while the monthly average was determined to be 22.3 vehicles per hour.

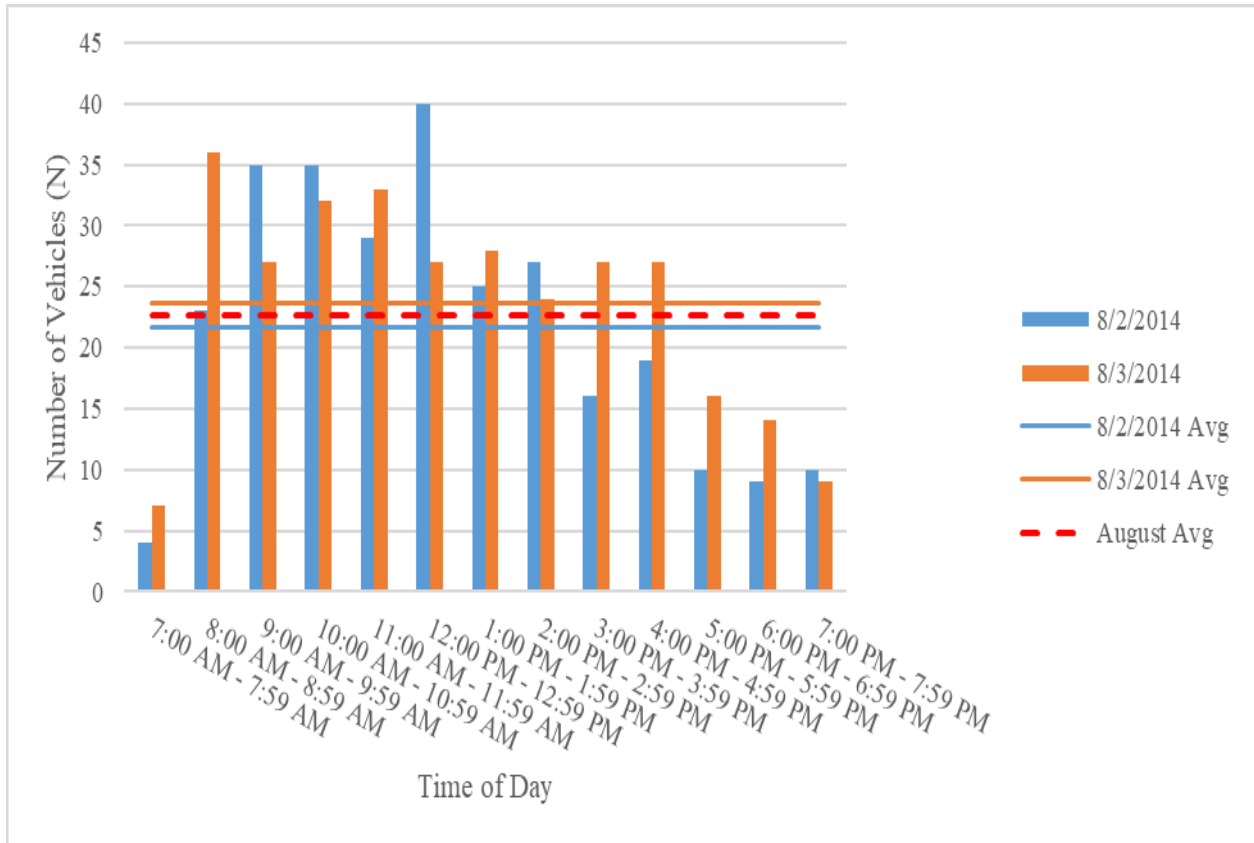


Figure 3-8 August 2014 LSR Vehicle Arrivals

The data collected in August 2014 consisted of two days of 13-hour observations. The dates of 8/2 and 8/3 correspond to Saturday and Sunday respectively. The maximum peak hour was observed at 40 vehicles per hour from 12:00 PM – 12:59 PM on Saturday 8/2, while the monthly average was determined to be 22.7 vehicles per hour.

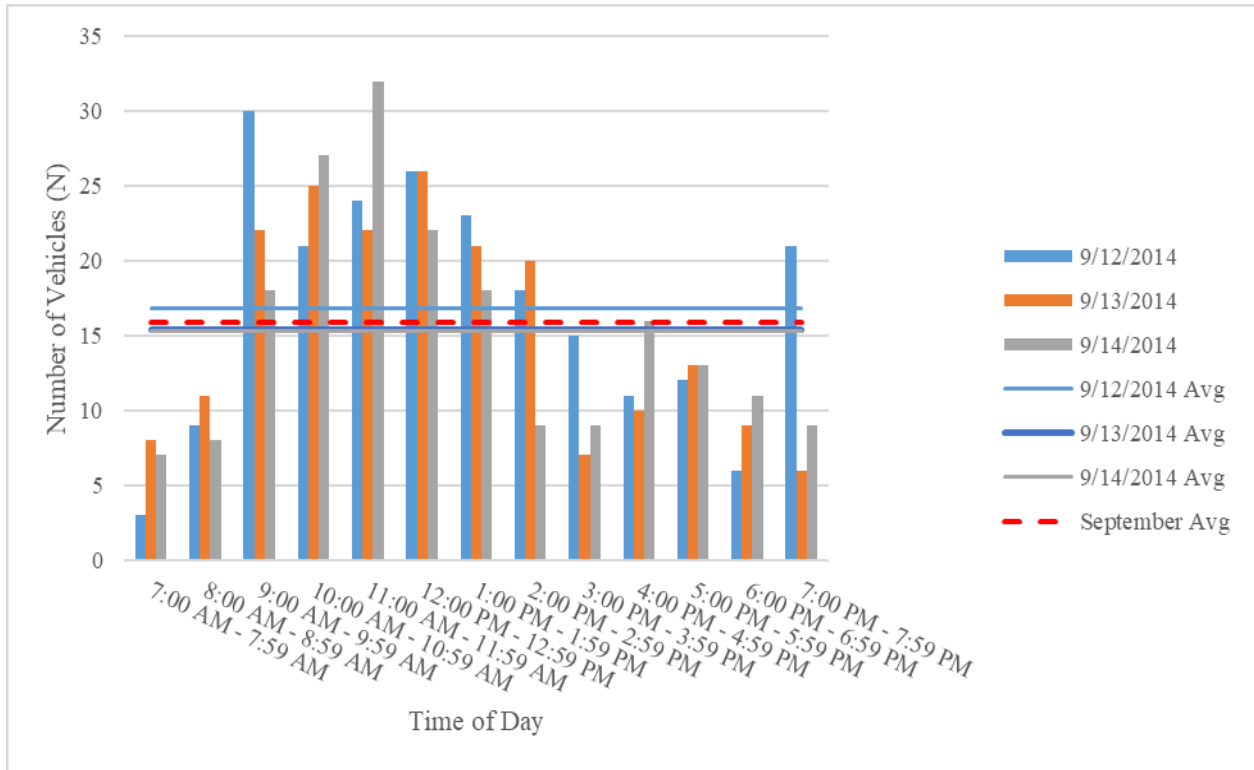


Figure 3-9 September 2014 LSR Vehicle Arrivals

The data collected in September 2014 consisted of three days of 13-hour observations. The dates of 9/12, 9/13 and 9/14 correspond to Friday, Saturday and Sunday respectively. The maximum peak hour was observed at 32 vehicles per hour from 11:00 AM – 11:59 AM on Sunday 9/14, while the monthly average was determined to be 15.9 vehicles per hour.

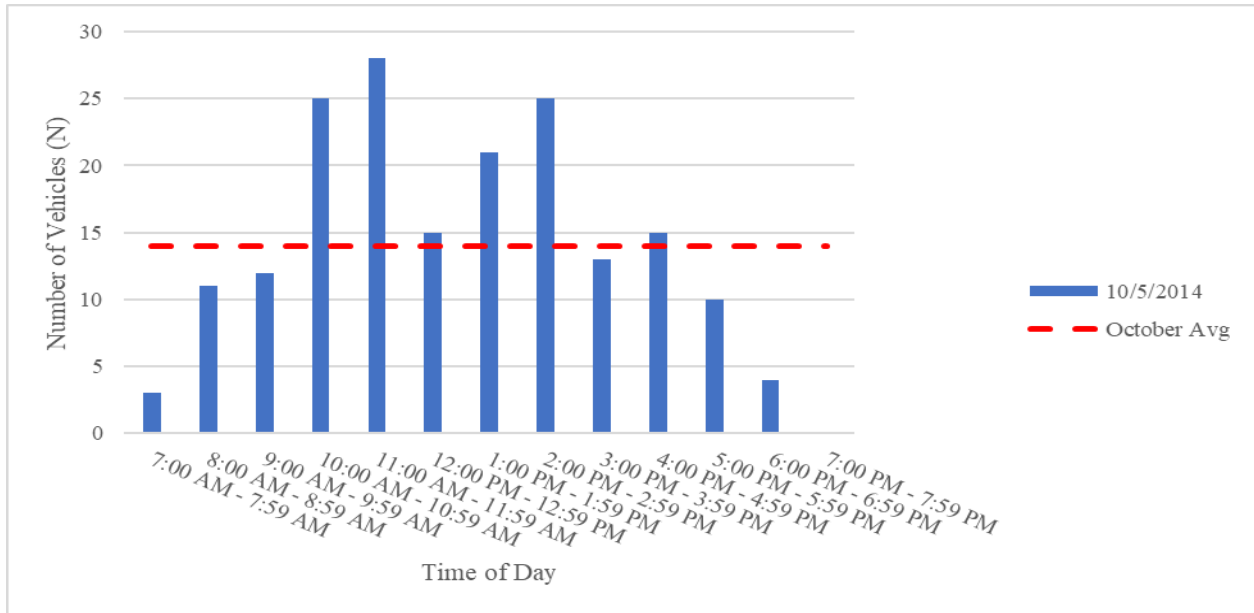


Figure 3-10 October 2014 LSR Vehicle Arrivals

The data collected in October 2014 consisted of a one day of 13-hour observation. The date of 10/5 corresponds to Sunday. The maximum peak hour was observed at 28 vehicles per hour from 11:00 AM – 11:59 AM on Sunday 9/14, while the monthly average was determined to be 14 vehicles per hour.

As observed from the above data, the peak hours varied over the eight months of data collection with three months having a peak hour at 10:00 AM, three months having a peak hour at 11:00 AM and the remaining at 12:00 PM and 1:00 PM. However, the majority of the vehicle arrivals occur between the times of 9:00 AM – 2:59 PM. Thus, the data within these six hours was further considered as the peak hours, and the average was determined for each month. The reasoning behind this approach allows for a higher arrival rate average to be considered and therefore provides more conservative parameters. Table 3-1 illustrates a summary of these results in terms of monthly arrival rates.

Table 3-1 Monthly Arrival Rates

Observation Period	13 Hour Average Hourly Arrival Rate (Vehicles/Hour)	9:00 AM - 2:59 PM Average Hourly Arrival Rate (Vehicles/Hour)
July 2013	21.90	31.54
August 2013	22.04	31.75
September 2013	24.12	34.38
June 2014	18.51	26.47
July 2014	22.31	32.22
August 2014	22.65	30.17
September 2014	15.85	22.44
October 2014	14.00	21.00

The time a vehicle spent parked at the LSR was determined through the use of GPS technologies. These data had previously been derived and published in technical reports provided to the GRTE in work provided by Monz et al. (*Monz et al. 2014; Monz et al. 2015*). The findings determined that for both the 2013 and 2014 summer and fall seasons, the average amount of time vehicles spent parked at the LSR was 1 hour and 20 minutes (80-minutes).

3.6 Analysis Methods

Parking at the LSR is evaluated as an *M/M/6I* system using Little’s law. In order to measure the performance, some terms need to be defined. First, the average arrival rate and service rate will be identified with the symbols of λ and μ respectively. Utilizing these two known values, the expected number of visitors in the system L_s , expected number of visitors in the queue L_q , expected waiting time in the system W_s , expected waiting time in queue W_q , and the expected number of busy servers/parking spaces c' (where c is the available number of

servers/parking spaces) which leads to identifying the facility utilization value can be determined. Equations 3-1 – 3-5 illustrate the relationships used to determine these measures of performance (*Taha 2007*).

$$L_s = \sum_{n=1}^{\infty} np_n = \lambda_{eff} W_s = L_q + \frac{\lambda_{eff}}{\mu} \quad \text{Eq. 3-1}$$

$$L_q = \sum_{n=c+1}^{\infty} (n - c)p_n = \lambda_{eff} W_q \quad \text{Eq. 3-2}$$

$$W_s = W_q + \frac{1}{\mu} \quad \text{Eq. 3-3}$$

$$c' = L_s - L_q = \frac{\lambda_{eff}}{\mu} \quad \text{Eq. 3-4}$$

$$\text{Facility Utilization} = \frac{c'}{c} \quad \text{Eq. 3-5}$$

The distinction of the effective arrival rate (λ_{eff}) and the average arrival rate (λ) presents itself in a system like the LSR parking. The average arrival rate can be thought as the average of all the observed volume of vehicles entering the LSR from the MWC. However, there is a possibility that the parking lot is full or fills during the arrival of vehicles. This situation would then result in a “loss” of vehicle arrivals (λ_{lost}), or vehicles that decide to leave the LSR parking because there is no availability. This relationship can be summarized by Equations 3-6 to 3-7 (*Taha 2007*).

$$\lambda_{lost} = \lambda p_c \quad \text{Eq. 3-6}$$

$$\lambda_{eff} = \lambda - \lambda_{lost} \quad \text{Eq. 3-7}$$

To further discuss the process of evaluating the LSR's parking performance, the explanation of the probabilities that compose the above-queueing measures of performance will be discussed. As previously stated, an LSR's system can be identified as a Poisson distribution with random arrivals and service rates. Thus, the Poisson probability distribution function can be referenced to estimate the probabilities of a vehicle occupying a parking space. Furthermore, seven parking spaces are considered as temporary locations where vehicles may wait temporarily until a parking space opens up. Equations 3-8 to 3-10 illustrate how the probabilities are determined for each event (parking spaces occupied).

$$\frac{\left(\frac{\lambda}{\mu}\right)^n}{n!} p_0, n = 1, 2 \dots 54 \quad \text{Eq. 8}$$

$$\frac{\left(\frac{\lambda}{\mu}\right)^n}{54!54^{n-54}} p_0, n = 54, 55 \dots 61 \quad \text{Eq. 9}$$

$$P_0 + P_1 + \dots + P_{61} = 1 \quad \text{Eq. 10}$$

3.7 Analysis and Results

Various parameters were considered during the evaluation in order to observe possible extreme cases of performance for the LSR parking system. The maximum average arrival rate observed during the 13-hour data collection period was during September 2013 with an average rate of 24.1 vehicles per hour. Similarly, the six-hour peak hour rate was observed in September 2013 at an average rate of 34.8 vehicles per hour. These two values were rounded up (25 and 35 vehicles per hour) and utilized as the average arrival rate and input into the queuing equations. Also, the arrival rate of 45 vehicles per hour was considered as an extreme case. Furthermore, the service rate was determined by referencing the average amount of time a vehicle spent

parked at the LSR. The value of 1 hour and 20 minutes (80 minutes) was the average service rate observed. However, an average service rate of 2 hours (120 minutes) and 3 hours (180 minutes) were also considered as extreme cases. Table 3-2 illustrates the measures of performance under these conditions.

Table 3-2 LSR Parking Queue Evaluation Results

λ (Veh/Hr)	μ (min)	λ_{lost}	λ_{eff}	L_s (Veh)	W_s (min)	W_s (HH:MM:SS)	L_q (Veh)	W_q (min)	W_q (HH:MM:SS)	c' (Spaces)	Facility Utilization
25	80	0.00	25.00	33.33	80.00	1:20:00	0.00	0.00	0:00:00	33.33	0.61
	120	0.69	24.31	49.53	122.24	2:02:15	0.91	2.24	0:02:15	48.62	0.88
	180	7.06	17.94	58.54	195.82	3:15:49	4.73	15.82	0:15:49	53.81	0.98
35	80	0.39	34.61	46.58	80.76	1:20:46	0.44	0.76	0:00:46	46.14	0.84
	120	8.18	26.82	57.91	129.54	2:09:32	4.27	9.54	0:09:32	53.65	0.98
	180	17.00	18.00	59.94	199.84	3:19:50	5.95	19.84	0:19:50	53.99	0.98
45	80	5.53	39.47	55.45	84.30	1:24:18	2.83	4.30	0:04:18	52.62	0.96
	120	18.02	26.98	59.51	132.34	2:12:20	5.55	12.34	0:12:20	53.96	0.98
	180	27.00	18.00	60.33	201.12	3:21:07	6.33	21.12	0:21:07	54.00	0.98

The above process provided a Poisson probability distribution function for each scenario. These distribution functions provide information on the probability of having n number of vehicles in the system. Figure 3-11 illustrates these results.

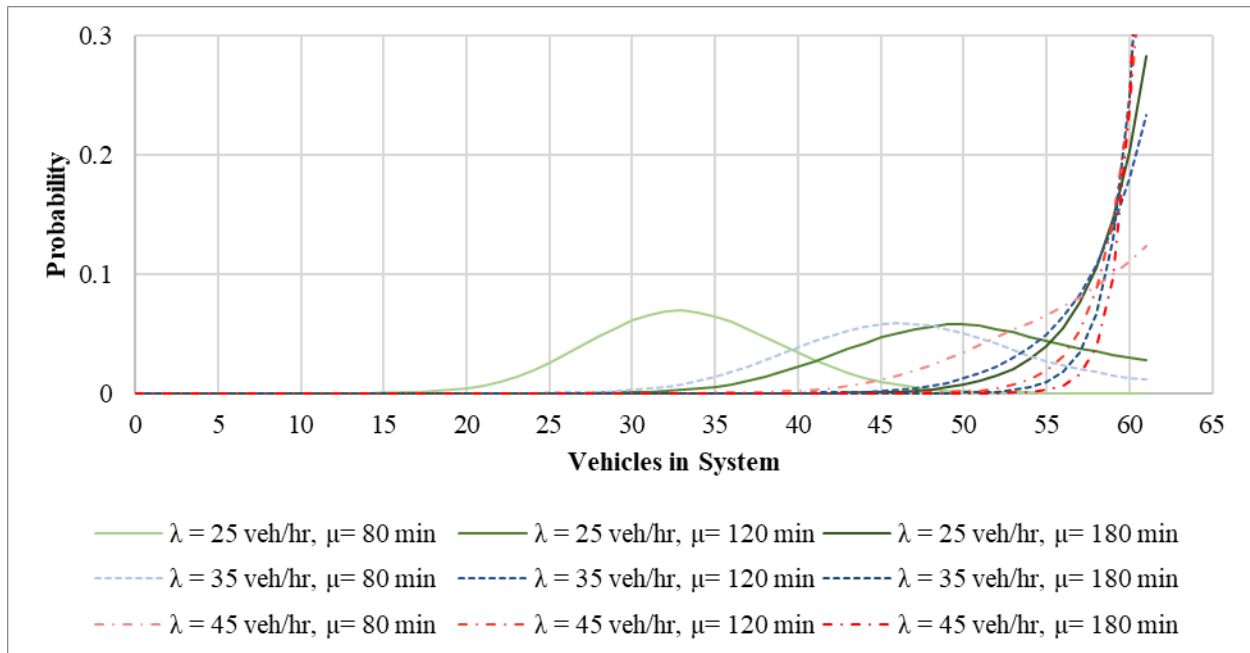


Figure 3-11 Probability Distribution Functions of Considered Arrival and Service Rates

The figures above illustrate a normal distribution for the cases of $\lambda = 25$ veh/hr and $\mu = 80$ minutes, $\lambda = 25$ veh/hr and $\mu = 120$ minutes, $\lambda = 35$ veh/hr and $\mu = 80$ minutes. These describe situations where the highest probability of n vehicles in the system are below the available number of parking spots. However, the remaining cases which were considered as the more extreme followed an exponential distribution. These suggest that, under the given arrival and service rates, the LSR's parking has a greater probability of reaching capacity for both the 54 available parking spaces and the seven temporary spaces, and in turn leading to high queue lengths, queue waiting time and visitor loss.

3.8 Discussion of Results

The average arrival rates and service rates which were observed ($\lambda = 25, 35$ veh/hr and $\mu = 1$ hour 20 min) provided acceptable results for the performance measures of the LSR parking

system, with the largest expected queue waiting time of 46 seconds. Overall, these results suggest that the LSR's current parking capacity is sufficient under the observed visitor arrivals.

However, as the results above suggest for the extreme cases, an increase of arrival rate to 45 veh/hr will begin to worsen the performance measures and increase both the anticipated vehicle queue length and queue waiting time. All of the service rates considered resulted in facility utilization values greater than 95% and a visitor loss greater than five veh/hr. Similarly, poor results were observed under the $\lambda = 25$ veh/hr with $\mu = 3$ hr and $\lambda = 35$ veh/hr with $\mu = 2$ hr and 3 hr.

Therefore, under the observed parameters, the LSR's parking is expected to perform well and have little queueing and little loss of visitor arrivals. Problems are expected to occur if the average arrival increases to 45 veh/hr or if the average time vehicles spend parked increased to greater than 2 hours. The seven parking spaces which were considered as a temporary parking area for "waiting" vehicles would only be utilized under the higher arrival and service rates. If the LSR is to experience an increase of arrival rates or vehicle parking time possible mitigation strategies include enforcing a parking time limit to keep the facility utilization at a reasonable value. Furthermore, overflow parking in an unpaved area is a possibility along with utilizing the temporary parking area as permanent parking spaces.

3.9 Conclusions

The LSR parking system can be evaluated as an M/M/54 without considering seven parking spaces as a temporary "waiting area" and, if considered, it would be referenced as an M/M/61. The queuing discipline is described as service in random order (SIRO), due to the uncertainty of vehicles arriving and leaving while other parking spaces are available. Arrival rate

data was collected by observing the intersection movement of MWC and the LSR entry road, and all movements south into the LSR were assumed to be the arrival rate. This data was collected for 13-hour periods during random days over eight months between the summer and fall season of 2013 and 2014.

It was determined that September 2013 provided the largest average arrival rate of 24.1 veh/hr. Similarly, the hours in which the most significant arrival rates were observed was between 9:00 AM – 2:59 PM. Considering these six hours, the average arrival rate was determined to be 34.4 veh/hr. The average time a vehicle spent parked (service rate) at the LSR was determined through reference to GRTE technical reports, in which the average time was found to be 1 hour and 20 minutes (80 minutes) for both 2013 and 2014 seasons.

The analysis consisted of using Little's law to determine the measures of performance for the LSR's parking system. This was completed under the observed conditions as well as larger average arrival and service rates, which were considered as extreme cases. Nine total analysis was conducted for the arrival rates of 25, 35 and 45 veh/hr each with a service rate of 1 hr 20 min (80 minutes), 2 hr (120 min) and 3 hr (180 min) in order to evaluate how the measures of performance would change.

Under the observed conditions, the LSR's parking system experiences good performance. Under an arrival rate of 25 veh/hr and an 80-minute service rate, the expected queue length and queue waiting time are zero. The normal average parking space usage is 33.3, and the facility utilization is 61%. Under an arrival rate of 35 veh/hr and an 80-minute service rate, the expected queue length remains low and the queue is waiting time anticipated to be 46 seconds. The expected average parking space usage is 46.1, and the facility utilization is 84%. The remaining cases resulted in poorer results with high anticipated visitor loss, vehicle queue length, and queue

waiting time. If higher arrival rates and service times were to be observed, possible solutions could include enforcement of time spent parked (service time) or providing overflow parking.

Lastly, this paper describes the steps and analysis methods to evaluate the measures of performance for a queueing system. With this information, the GRTE can re-evaluate the LSR parking queue and facility utilization estimates based on visitor changes and different seasons. This process is also applicable to any other parking area within a national park or in general where queues may be anticipated. By utilizing the methodology outlined above with data that can be obtained relatively easily, levels of use can be determined. With this information, national parks can make better-informed decisions relating to the expansion of parking facilities or management of parking by visitors by setting timed parking spaces.

3.10 Applying Findings into an Agent-Based Model

Applying the methodology discussed in this chapter to an ABM requires the consideration of two main aspects. One is the number of vehicles that are expected to visit the LSR and the second is the duration of time they will spend there. As discussed in the previous sections, under observed conditions the LSR's parking operations appear to be in good condition as queue waiting time and vehicle queueing is low. However, tying in the findings from Chapter 2 allows us to determine a proportion of agents (vehicles) that are likely to stop at the LSR attraction after passing through the entrance stations and spending a determined amount of time at this attraction.

Thus, instructing agents (vehicles) to stop at the LSR would consist of assigning a random number between 0 – 1 and based on certain thresholds be instructed to stop at the LSR (i.e., $0 - .15 = 15\%$ proportion of vehicles in the MWC will turn into the LSR and spend parked

time at this attraction). Instructing the agents to spend time at the LSR is accomplished by encoding rules that enforce the agent to hold their position for a determined amount of time. The time can be determined from a random draw from a normal distribution bounded by the mean value and standard deviation of collected data.

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4 CHAPTER 4: A Decision Tree Approach to Predicting Vehicle Stopping from GPS Tracks in a National Park Scenic Corridor

This chapter is adapted from Fuentes, A., Heaslip, K., Sisneros-Kidd, A. M., D'Antonio, A. Kelarestaghi, K. B. (*In Review*) A Decision Tree Approach to Predicting Vehicle Stopping from GPS Tracks in a National Park Scenic Corridor. Transportation Research Record.

4.1 Introduction

National parks are an essential part of the lands that make up the United States as they provide leisure alternatives that promote the nation's history and importance of preservation. From a transportation perspective, they present a unique system in which different behaviors can be observed when time constraints and delays are not as pressuring as an urban environment. Scenic corridors at national parks provide an exciting challenge as they often carry the most history, require the most preservation and often see the most significant visitor demand. This study is focused on evaluating one such scenic corridor in Grand Teton National Park (GRTE), the Moose-Wilson Corridor (MWC). GRTE has three entry stations, one of which is in the MWC. The MWC can be entered from a south entry point near Teton Village, a popular resort which is outside the boundaries of GRTE, or through a north entry point near GRTE headquarters. The corridor itself includes asphalt and gravel surface types and is regulated at the 35-mph speed limit. The MWC corridor spans a total of 7.7 miles and is required to be traveled to reach some of the primary attractions of GRTE which include the Death Canyon and Granite Canyon trailheads, the Laurance S. Rockefeller Preserve (LSR) and Sawmill Ponds overlook

(Service 2017). Figure 4-1 illustrates a map of the MWC area along with the described attractions.

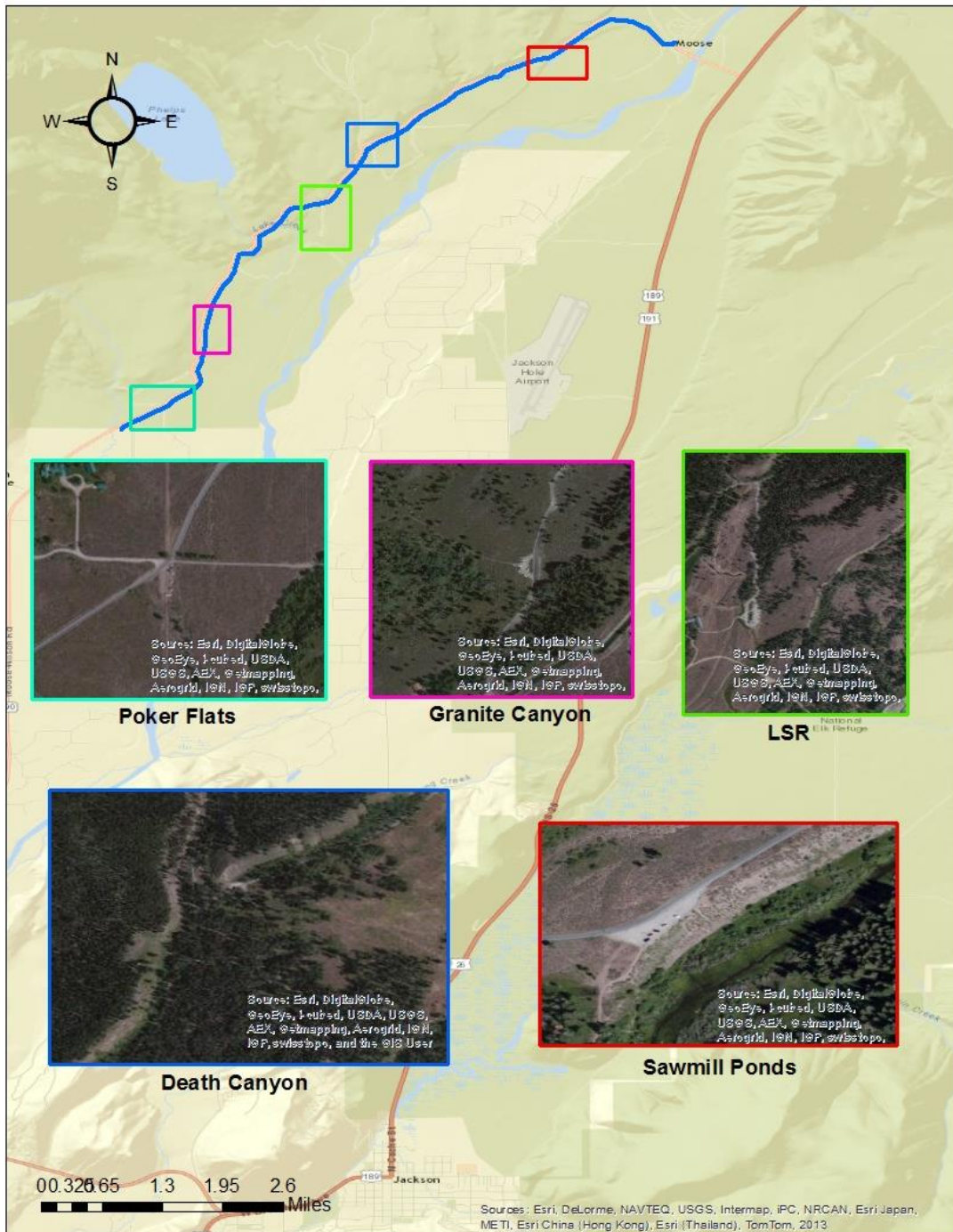


Figure 4-1 The Moose-Wilson corridor and its attractions

Previous research and data collection methods on national park scenic corridors have utilized survey and GPS-based tracking methods to emphasize the behavioral aspects of visitors and how their time is spent and distributed. Survey methods of data collection have been highlighted by Pettebone et al. for Bear Lake Road in Rocky Mountain National Park through a stated choice survey aiming to estimate travel mode choices (*Pettebone et al. 2011*). GPS-based tracking methods have been presented and implemented by D'Antonio et al. (*D'Antonio et al. 2010*) for three national park locations which include Bear Lake Road at Rocky Mountain National Park, Tuolumne Meadows trail in Yosemite National Park and the Teton Range for analysis of visitor use, spatial patterns and recreation. In this study, GPS tracking data collected from visitors during the 2013 and 2014 seasons will be utilized to predict the probability that a visitor in a vehicle stopped at one of the considered attractions of the MWC. This paper aims to visualize, assess, and predict the probability of vehicles stopping along the MWC corridor through the implementation of decision tree methodologies. Utilizing such an approach in a national park setting provides park management, scientists and engineers with two critical resources. First, this paper provides a reference to implementing a decision tree analysis from available GPS-tracks and discusses how it can assist in decision-making strategies. Additionally, it provides a glimpse of new machine learning methods that are becoming more applicable as technology continues to advance, and data becomes more readily available.

A benefit to the use of a decision tree methodology in the MWC and general national park settings is that the results are easily interpreted and relationships between variables are quickly identified. Additionally, it provides an appropriate study of a behavior that is common in a national park scenic corridor setting while providing a glimpse of data analytic capabilities. Advancement in technology has allowed for data to be more easily accessed and analyzed. Data

of interest in the field of transportation includes time-sensitive vehicle counts to determine temporal variation in volume and can now be collected through various advanced technology. Spatial data collection has also been facilitated through mobile technology with GPS capabilities and provides rich data for transportation planners and engineers. These data are available in various formats, through different sources, and can provide greater accuracy in planning and developing decision-making strategies. The contribution presented in this paper consists of demonstrating how GPS tracking data can be used to build a decision tree capable of informing park management of the probabilities that a visitor in a vehicle will stop at an attraction. In this paper, the scenic corridor is the MWC, and the attractions of interest include Death Canyon, Granite Canyon, LSR and Sawmill Ponds. Furthermore, the study incorporates a non-parametric machine learning approach to a unique national park setting where more significant variation in visitor behavior is observed. Finally, the results and methods implemented can aid national park managers in understanding current system behavior, identify relationships, and plan for future policy decision-making strategies.

The remainder of this paper is organized into four sections; the first provides a literature review of relevant national park studies, GRTE focused transportation research and decision tree applications. The second provides an overview of the study data, explanation of the considered variables, and explanation of the analysis structure. The third provides the results and discussion, while the last section summarizes and concludes the paper and findings.

4.2 Literature Review

National parks provide a rich environment for conducting research studies related to recreation, ecology, history, and anthropology. Similarly, they are a unique setting for

researching transportation from a different perspective, where the daily constraints and pressure of reducing delay are relaxed, and different driver behavior can be observed. Early transportation studies conducted in national park settings include work by Upchurch who examined entrance station capacity and service times as well as parking limitations and mode alternatives at various national parks (*Upchurch 2006; Upchurch 2015*). Upchurch's findings identified differences and limitations observed at entrances and on scenic roadways, such as the seasonal variation of visitors and differences throughout the time of day.

Similarly, Hallo et al. focused on a national park setting by investigating the social carrying capacity of a scenic road corridor at Acadia National Park through quantitative survey approaches, simulation, and evaluating driving for pleasure in a scenic roadway (*Hallo and Manning 2009; Hallo and Manning 2010*). Hallo's contribution presented corridor specific findings which helped to visualize how visitors perceive road capacity as well as one of the first discussions of GPS devices used for data collection and simulation modeling purposes.

Additionally, D'Antonio et al. (*D'Antonio et al. 2010*) provided detailed case studies of GPS-based tracking capabilities in three different national parks where GPS-based tracking methods, applications, and protocols are detailed. Findings determined that GPS-based tracking methods were promising as more detailed spatial and temporal data was obtained by GPS technology over traditional methods. Kidd et al. (*Kidd et al. 2015*) implemented a GPS-based tracking method in Acadia National Park to further understand visitor behavior during recreational activities through educational strategies. Kidd et al. used GPS tracks to evaluate off-trail travel by visitors after receiving information and educational messages from different sources which included personal contact and various forms of messaging.

Recently, various studies focusing on GRTE have been published which further capture the unique importance of its transportation system and visitor behavior. During the 2013 and 2014 season, GRTE released technical reports written by Monz et al. regarding the visitor use levels, types, patterns and impacts seen in the MWC (*Monz et al. 2014; Monz et al. 2015*). From the data collected by Monz et al., (*Monz et al. 2014; Monz et al. 2015*) additional studies have been published which have developed management strategies and recommendations for the MWC in GRTE. Fuentes et al. evaluated the queuing levels at the Laurance S. Rockefeller Preserve (LSR) on the MWC. The methodology of their work aimed to estimate the parking utilization based on visitor arrival rates and determined that an observed arrival rate of 25 vehicles per hour and an 80-minute service rate resulted in a facility utilization of 61% (*Fuentes et al. 2017*). Furthermore, a stated choice approach was utilized by Newton et al. (*Newton et al. 2017*) through survey methods to investigate transportation attributes important to visitors at the MWC, determining that parking availability was the highest importance over waiting time at the entrance, speed of traffic, and volume of traffic. Finally, Kidd et al. (*Kidd et al. 2018*) utilized GPS tracks collected from the MWC and a multivariate statistical approach to evaluate patterns of vehicular visitation along its attractions and ultimately determined that visitors can be classified into three categories, opportunistic commuters, wildlife/scenery viewers, and hikers.

The work presented in this paper differs from previously published MWC studies as it utilizes and outlines a decision tree methodology which is a non-parametric classification approach and intends to predict the probability of vehicles stopping at various attractions throughout the MWC. Decision trees are part of a broader scope of computational strategies and data analysis methods that have seen a recent increase in use and application as data acquisition has become more readily available. The definition of data analytics has been described to be an

“interdisciplinary field that has adopted aspects from many other scientific disciplines such as statistics, signal theory, pattern recognition, computational intelligence, machine learning, and operations research” (*Runkler 2012*). With its interdisciplinary capabilities, decision trees have been used to address various transportation problems. A few worth noting include work by Zheng et al. (*Zheng et al. 2016*) which implemented a decision tree approach to predict accidents at highway-rail grade crossings. In their model 23 variables were considered as explanatory variables and final accuracies were determined to be 77.2% for predicting accuracies of crossing without a crash and 84.1% for predicting crossings with a crash.

Similarly, Qiao et al. (*Qiao et al. 2017*) used a decision tree approach to determine when post flooded roads should be opened, focusing more on the factors or variables that influence the tree structure and ultimately identifying true structural state after flooding, demand for connectivity, and worst-case consequences. Although the work presented uses a previously collected dataset, it is not farfetched to assume that soon data collection methods will see greater automation and will be able to predict visitor behavior in real-time more rapidly. Thus, the methodology and procedures presented in this study will aid in providing park managers the opportunity to glimpse and prepare for future technological capabilities.

4.3 Data Collection

The data used for this study was collected by a team of Utah State University and Penn State University researchers over a three-month period (July - September) in 2013 and a five-month period (June - October) in 2014 (*Kidd et al. 2018; Monz et al. 2014; Monz et al. 2015*). A random stratified sample of visitors was asked to participate in the study voluntarily. Following procedures outlined by D’Antonio et al., each visitor willing to contribute to the study was given

a Garmin eTrex 10 GPS unit that would track the vehicle movement every 10 seconds along the MWC (*D'Antonio et al. 2010*). The GPS unit was given to the visitor upon entry (at both north and south entry points) to the MWC, and each visitor was asked to return the unit upon exiting the corridor. Only one GPS unit was allotted per vehicle regardless of the number of visitors at the party. Thus each vehicle represented one observation.

During the two-year sample period, a total of 547 observations were collected for 2013 and 869 observations were collected for 2014 totaling 1,416 observations. Since the primary interest of this paper is attempting to predict when a vehicle stopped in one of the corridor attractions, the data was refined to sub-sets focusing only on vehicles that stopped while in the MWC. Stopping in this study was defined as no vehicle movement for 10 seconds or more, due to visitor behavior often consisting of stopping only to view wildlife and scenery and then advancing through the corridor (*Kidd et al. 2018; Monz et al. 2014; Monz et al. 2015*). Overall, it was determined that for the year 2013, 278 out of 547 observations could be evaluated and for the 2014 year, 536 out of 869 observations could be evaluated, resulting in a combined sample set of 814 observations.

Furthermore, the percentage of vehicles that stopped at the considered attractions in the MWC from the refined sample set determined that 9.7% stopped at Death Canyon, 12.9% stopped at Granite Canyon, 40.8% stopped at LSR, and 65.7% of the observed vehicles stopped at Sawmill Ponds. Figure 4-2 illustrates a summary of these findings. Table 1 below describes the variables that were used from the GPS tracks and were considered for the building of the decision tree model.

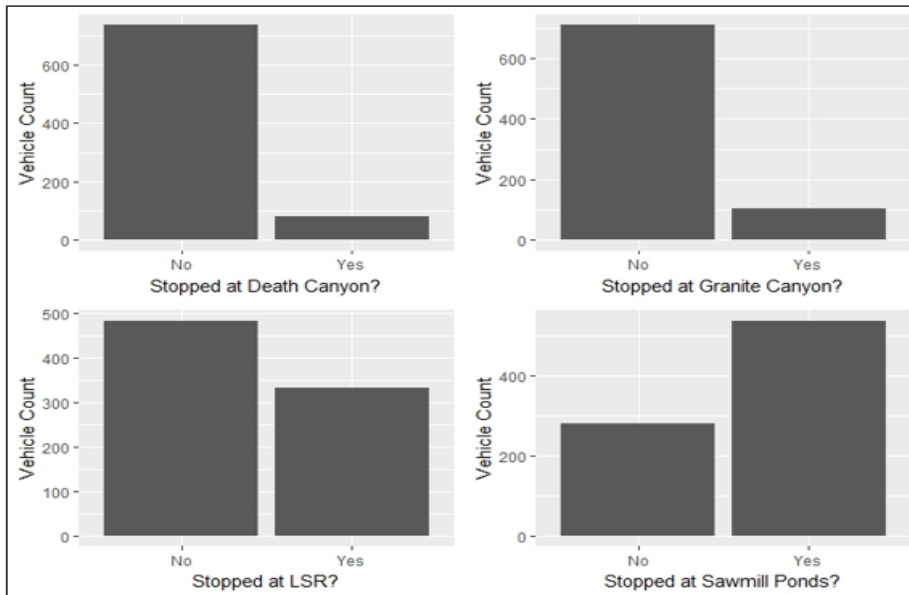


Figure 4-2 Distribution of vehicle stops at MWC attractions

4.4 Decision Tree Methodology

Decision tree approaches are a non-parametric approach to classification of data. Non-parametric strategies are often utilized when the data does not meet the assumptions of normality that are often imposed in frequentist statistics. Thus non-parametric statistics can be described as “distribution-free since they make no underlying assumptions of the data” (*Boslaugh and Watters 2008*). Such an approach is suitable in this data as multicollinearity issues between variables may be present in vehicles that stop at similar attractions.

The decision tree methodology consists of identifying a variable that has the most substantial relationship to the response variable and is then set as the parent node of the tree. From there, child nodes are identified depending on the algorithm implemented until some stopping criteria are met. Tree split points are determined through a purity assessment, by

ensuring that the population of the sub-partition is as pure as possible. Two measures of purity discussed by Kassambara, include the Gini index and the Entropy, illustrated in Equation 4-1 and Equation 4-2 respectively, where p is the proportion of misclassified observations. Both indices range from 0 to 1, where 0 signifies the highest purity and 1 the greatest impurity (*Kassambara 2018*). The decision tree methodology was implemented in this study through the R software, by utilizing the “rpart” (recursive partitioning and regression trees) package and applying the Classification and Regression Trees (CART) algorithm (*Kassambara 2018; Team 2015; Therneau et al. 2010*).

Table 4-1 Summary of variables collected by GPS and considered for the study

Variable Name	Descriptive	Avg.	Std. Dev.
Year	1: 2013, 2: 2014	2013.66	0.47
Ent_Fr	1: Entry from North, 0: Entry from South	0.52	0.50
Ex_Fr	1: Exit from North, 0: Exit from South	0.65	0.48
Stop_DC	1: Vehicle Stop at Death Canyon, 0: Otherwise	0.10	0.30
Stop_GC	1: Vehicle Stop at Granite Canyon, 0: Otherwise	0.13	0.34
Stop_LSR	1: Vehicle Stop at LSR, 0: Otherwise	0.41	0.49
Stop_PF	1: Vehicle Stop at Poker Flats, 0: Otherwise	0.05	0.22
Stop_SP	1: Vehicle Stop at Sawmill, 0: Otherwise	0.66	0.47
Ent_BefNoon	1: Vehicle Entered Before Noon, 0: Otherwise	0.54	0.50
Ex_BefNoon	1: Vehicle Exit Before Noon, 0: Otherwise	0.33	0.47
Ent_0_4	1: Vehicle Entered between 12 AM – 4 AM, 0: Otherwise	0.00	0.00
Ent_4_8	1: Vehicle Entered between 4 AM – 8 AM, 0: Otherwise	0.01	0.11
Ent_8_12	1: Vehicle Entered between 8 AM – 12 PM, 0: Otherwise	0.52	0.50
Ent_12_16	1: Vehicle Entered between 12 PM – 4 PM, 0: Otherwise	0.46	0.50
Ent_16_20	1: Vehicle Entered between 4 PM – 8 PM, 0: Otherwise	0.00	0.06
Ent_20_0	1: Vehicle Entered between 8 PM – 12 AM, 0: Otherwise	0.00	0.04
Ext_0_4	1: Vehicle Exited between 12 AM – 4 AM, 0: Otherwise	0.00	0.04
Ext_4_8	1: Vehicle Exited between 4 AM – 8 AM, 0: Otherwise	0.00	0.00
Ext_8_12	1: Vehicle Exited between 8 AM – 12 PM, 0: Otherwise	0.33	0.47
Ext_12_16	1: Vehicle Exited between 12 PM – 4 PM, 0: Otherwise	0.50	0.50
Ext_16_20	1: Vehicle Exited between 4 PM – 8 PM, 0: Otherwise	0.16	0.37
Ext_20_0	1: Vehicle Exited between 8 PM – 12 AM, 0: Otherwise	0.00	0.05
LocRes	1: Driver is a local resident, 0: Otherwise	0.14	0.34
RentVeh	1: Vehicle is a rental car, 0: Otherwise, NA if undetermined	0.30	0.46
GrpSz	1: group size ≥ 1 , 0: Otherwise, NA if undetermined	2.74	1.82
TT (Minutes)	1: Total Time vehicle spent in Corridor ≥ 0 , 0: Otherwise	85.55	85.70

$$Gini = \sum p(1 - p) \quad \text{Eq. 4-1}$$

$$Entropy = \sum -p(\log(p)) \quad \text{Eq. 4-1}$$

4.5 Model Implementation and Determination of Accuracy

The implementation of the decision tree methodology consisted of two key steps. First, identification of the response variables consisted of selecting four response variables which are stopping at Death Canyon, Granite Canyon, LSR and Sawmill Ponds. It must be noted that the same dataset was utilized on each of the response variables and re-implemented. Therefore, each of the response variables is also predictor variables in another model. This structure allowed the capture of possible attractions and destinations that may share similar visitation trends. For example, if results show that visitors enter from the north entry and stop at Sawmill Ponds and then stop at Death Canyon, it is a logical sequence since Death Canyon is the next attraction along the MWC.

Second, the total dataset of 814 observations was randomly shuffled and split into two sets containing 80% and 20% of the observations. Thus, the training set consisted of 651 observations (80%), and the testing set consisted of 163 observations (20%). The shuffling and splitting procedure was completed for each of the response variables of interest. After the decision tree model had been obtained utilizing the training set, the model itself was implemented on the test set. Thus, a predicted and actual result was available for comparison along with true negative, true positive, false negative and false positive values.

The predicted and actual results allow for the performance evaluation of the models which in turn provide measures to assess the model and better understand the data. The model accuracy can be determined through the formula illustrated in Equation 4-3 and can be interpreted as the overall frequency of correctly classified predictions provided by the model. The model precision is illustrated in Equation 4-4 and can be interpreted as the probability that a

positive observation is correct when predicted as positive. The model recall or sensitivity is illustrated in Equation 4-5 and can be interpreted as the probability that a positive observation is correctly recognized by the model. Finally, the specificity is illustrated in Equation 4-6 and is the recall on negative examples, meaning the probability that an observation which is truly negative will be correctly recognized by the model. In the equations below, N_{TP} is the number of true positives, N_{TN} is the number of true negatives, N_{FP} is the number of false positives and N_{FN} is the number of false negatives (*Kubat 2015*).

$$Accuracy = \frac{N_{TP} + N_{TN}}{N_{FP} + N_{FN} + N_{TP} + N_{TN}} \quad \text{Eq. 4-3}$$

$$Precision = \frac{N_{TP}}{N_{TP} + N_{FP}} \quad \text{Eq. 4-4}$$

$$Recall/Sensitivity = \frac{N_{TP}}{N_{TP} + N_{FN}} \quad \text{Eq. 4-5}$$

$$Specificity = \frac{N_{TN}}{N_{TN} + N_{FP}} \quad \text{Eq. 4-6}$$

4.6 Analysis and Results

A total of 25 explanatory variables (illustrated in Table 4-1) were run dependent on each of the four response variables of stopping at the Death Canyon, Granite Canyon, LSR and Sawmill Ponds. Before the analysis was started, an investigation of the response variable distributions was completed for the original dataset of 814 observations. Figure 3 illustrates the distribution of the explanatory variables that were found to influence the structure of the decision tree as well as some that were anticipated to affect. From Figure 4-3, it can be observed that 2014 saw a more

significant number of sampled visitors, while the north and south entry/exit points resulted in a similar number of observations. The time spent in the corridor resembles a left-skewed distribution with most of the vehicles spending under 50 minutes in the corridor and a median value of 42 minutes. Finally, the resident observations revealed a higher number of non-residents and some unidentifiable observations, while the rental vehicle observations similarly illustrated a greater amount of non-rental vehicles, but also a more significant amount of unidentifiable observations.

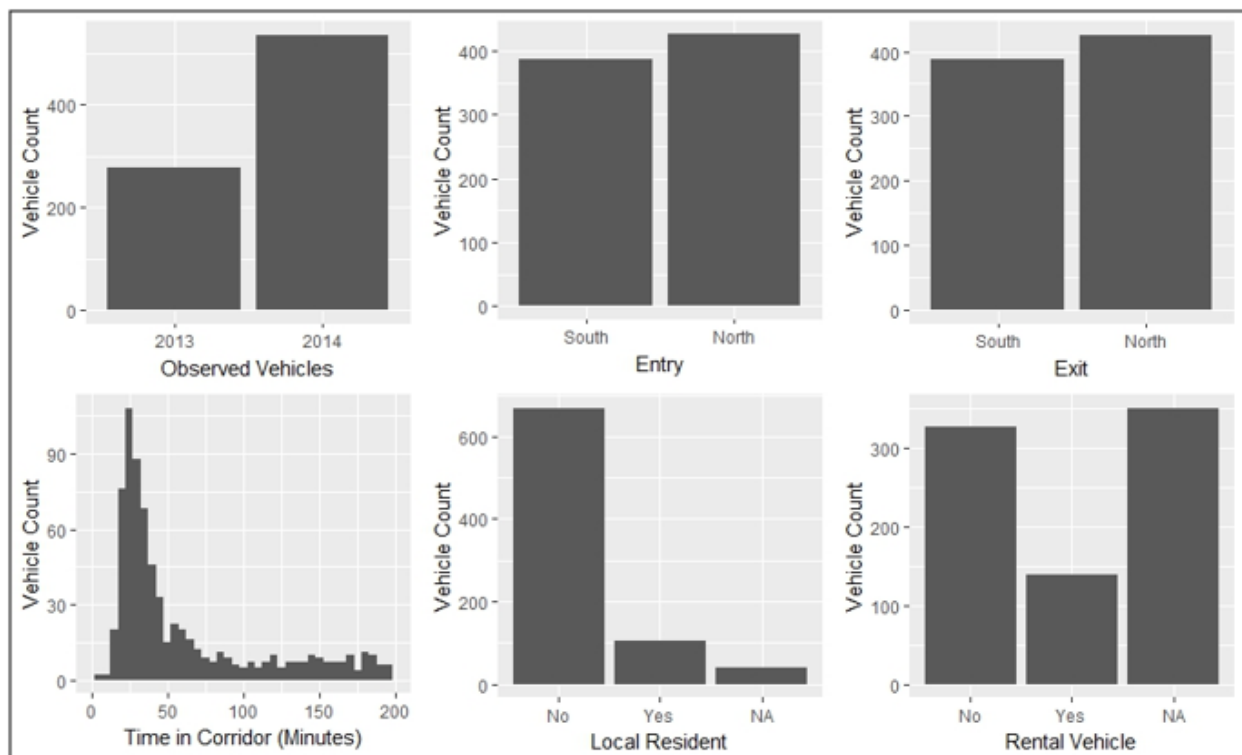


Figure 4-3 Distribution of Considered Explanatory Variables

Following, Figures 4-4 to 4-7, and Tables 4-2 to 4-5 present the decision tree model, confusion matrix, and performance evaluation results for Death Canyon, Granite Canyon, LSR and Sawmill Ponds, respectively. In Figures 4-4 to 4-7 below, the decision tree nodes

represented the explanatory variable with the greatest purity, followed by their binary responses, and response and predicted probability where 0 is the lowest probability, and 1 is the greatest probability. To describe the decision tree interpretation procedure, the Granite Canyon decision tree model will be thoroughly discussed. The same procedure of interpretation can be applied to the remaining Death Canyon, LSR, and Sawmill Ponds models.

In the Granite Canyon results, the first parent node identified in the decision tree was the exit location, meaning that if a vehicle exited from the north, there is a predicted probability of 0.92 that the vehicle *did not* stop at Granite Canyon. The following child node was stopping at LSR, meaning that if a vehicle exited from the south and stopped at LSR, then there is a predicted probability of 0.86 that the vehicle *did not* stop at Granite Canyon. The following child node was stopping at Sawmill Ponds; thus if a vehicle exited from the south, *did not* stop at LSR but *did* stop at Sawmill Ponds, then there is a predicted probability of 0.84 that the vehicle *did not* stop at Granite Canyon. Lastly, the last node was determined to be stopping at Death Canyon. Therefore, if a vehicle exited from the south, *did not* stop at LSR, *did not* stop at Sawmill Ponds and *did* stop at Death Canyon, then the predicted probability that the vehicle *did not* stop at Granite Canyon is 0.79, otherwise if it *did not* stop at Death Canyon then the predicted probability that it *did* stop at Granite Canyon is 0.74.

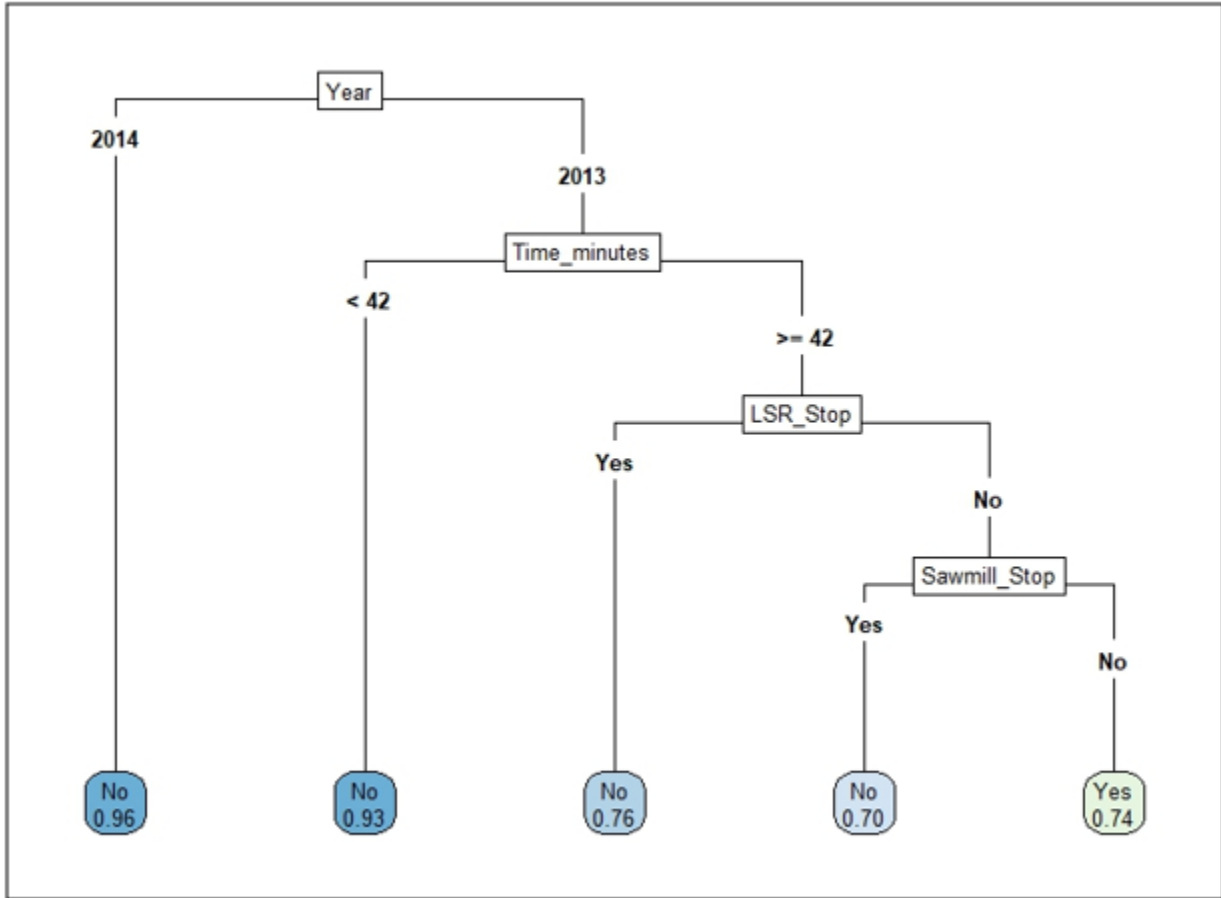


Figure 4-4 Decision tree for Death Canyon stop as the response variable

Table 4-2 Confusion matrix for Death Canyon model

		Did Vehicle Stop at Death Canyon?	
		Predicted	
		No	Yes
Actual	No	150	1
	Yes	8	4
Accuracy		94%	
Precision		80%	
Recall/Sensitivity		33%	
Specificity		99%	

The Death Canyon decision tree model consisted of four nodes, where the year variable was the parent node, and travel time in the corridor, stopping at LSR, and stopping at Sawmill Ponds were its child nodes. The Death Canyon model predicted the probability of stopping favored spending more than 42 minutes in the corridor, not stopping at LSR and not stopping at Sawmill Ponds. A possible interpretation could be that most visitors that stop at Death Canyon do so in anticipation of spending more than 42 minutes at the attraction. Therefore, the purpose of the visit to MWC could be categorized as visitors planning on participating in time-dependent recreational activities such as hiking. The small proportion of actual stops (12) and the behavior of not stopping at other locations also suggests that visitors are in MWC for the sole purpose of Death Canyon. Lastly, the parent node (i.e., year variable) suggests that in 2014, the Death Canyon had a very low predicted probability of stopping. This could be explained by seasonal effects at GRTE or possibly weather-related factors.

The Death Canyon decision tree model performance evaluation resulted in an accuracy of 94%, a precision of 80%, a recall of 33% and specificity of 99% with eight false negatives and one false positive. The model results indicated a high accuracy (94%) in terms of correct classification, and a high precision rate (80%) for classifying vehicles that stopped correctly. There is a 33% probability that the model will correctly identify a vehicle which stopped and a 99% probability that the model will correctly identify vehicles which did not stop. Therefore, there is a high certainty that the model can correctly identify vehicles that do not stop; however, the model does not perform as well when predicting vehicle stopping patterns.

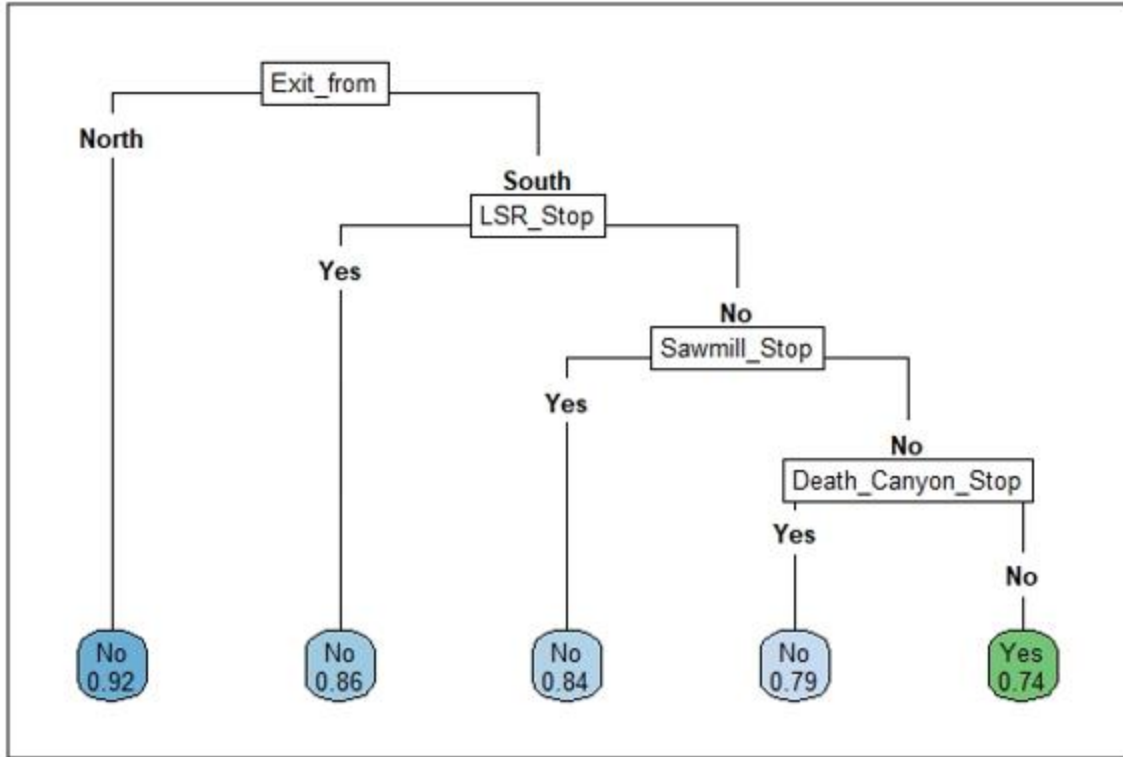


Figure 4-5 Decision tree for Granite Canyon stop as the response variable

Table 4-3 Confusion matrix for Granite Canyon model

		Did Vehicle Stop at Granite Canyon?	
		Predicted	
		No	Yes
Actual	No	142	5
	Yes	11	5
Accuracy		90%	
Precision		50%	
Recall/Sensitivity		31%	
Specificity		97%	

The Granite Canyon decision tree model consisted of four nodes, where the exit location was the parent node, and stopping at LSR, stopping at Sawmill Ponds and stopping at Death Canyon were its child nodes. The Granite Canyon model predicted a probability of stopping favored by not stopping at LSR, not stopping at Sawmill ponds, and not stopping at Death Canyon. The

Granite Canyon entrance was determined to be bound by the exit location. Since it is on the southern section of MWC and since the visitor data does not demonstrate stopping anywhere else, it would be reasonable to assume that Granite Canyon visitors enter and exit from the southern location. The Granite Canyon attraction exhibited similar behavior to the Death Canyon attraction in that the proportion of vehicles that stopped was low. Thus, a possible interpretation is that visitors with intentions of visiting Granite Canyon travel on the MWC for that reason.

The Granite Canyon decision tree model performance evaluation resulted in an accuracy of 90%, a precision of 50%, a recall of 31% and specificity of 97% with 11 false negatives and five false positives. The model results in high accuracy (90%) in terms of correct classification, but the precision of classifying vehicles that will stop correctly is only 50%. There is a 31% probability that the model will correctly identify a vehicle which stopped and a 97% probability that the model will correctly identify vehicles that did not stop. Therefore, the model performance is similar to the Death Canyon model in that the model performs better when identifying vehicles that do not stop. The lower precision of 50% for classifying vehicles that stopped correctly is lower than desired, but the high specificity would favor classifying vehicles as not stopping at Granite Canyon.

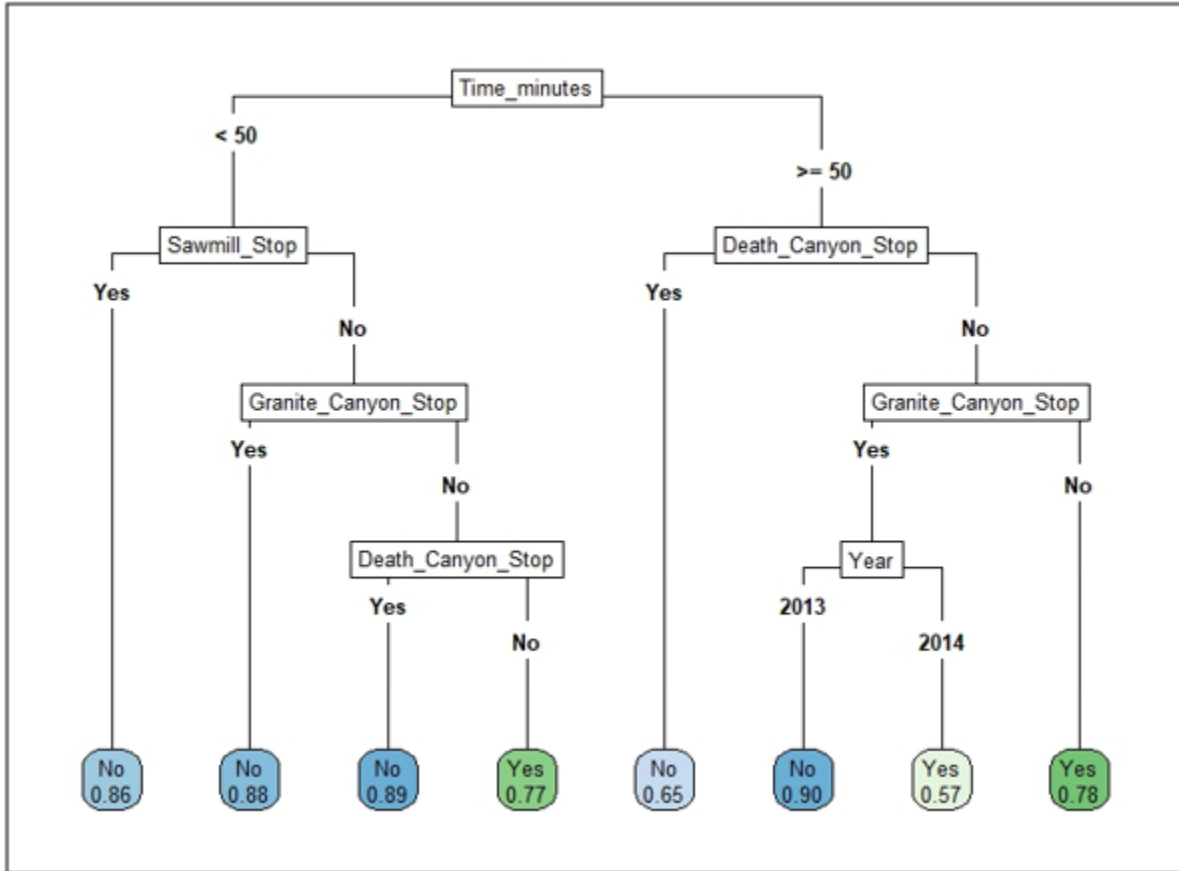


Figure 4-6 Decision Tree for LSR Stop as the Response Variable

Table 4-4 Confusion matrix for LSR model

		Did Vehicle Stop at LSR?	
		Predicted	
		No	Yes
Actual	No	75	20
	Yes	19	49
Accuracy		76%	
Precision		71%	
Recall/Sensitivity		72%	
Specificity		79%	

The LSR decision tree model consisted of seven nodes, where the time spent in the corridor was the parent node and the remaining attractions of Granite Canyon, Death Canyon, Sawmill ponds, and the year were its child nodes. The LSR model predicted a higher probability

of stopping if vehicles spent less than 50 minutes in MWC and did not stop at Sawmill Ponds, Granite Canyon or Death Canyon. Similarly, if vehicles spent more than 50 minutes and did not stop at Death Canyon or Granite Canyon, stopping at LSR saw a higher probability. Overall, results for stopping at LSR tend to favor not stopping at the other attractions. Additionally, there appears to be a seasonal effect for the year of 2014 as there was a predicted probability of 0.57 of stopping at LSR if the vehicle had also stopped at Granite Canyon.

The LSR decision tree model performance evaluation resulted in an accuracy of 76%, a precision of 71%, a recall of 72% and specificity of 79% with 19 false negatives and 20 false positives. The model captures the different behavior that was previously observed in the Granite Canyon and Death Canyon models in that more vehicles are stopping. The model results indicate a drop in accuracy in terms of correct classification at 76%, but the precision in classifying vehicles that will stop correctly is more significant than what was previously observed at 71%. There is a 72% probability that the model will correctly identify a vehicle which stopped and a 79% probability that the model will correctly identify vehicles which did not stop. Therefore, in terms of recall and correctly classifying vehicles that stop at LSR, the model performs much better than the previous Granite Canyon and Death Canyon models.

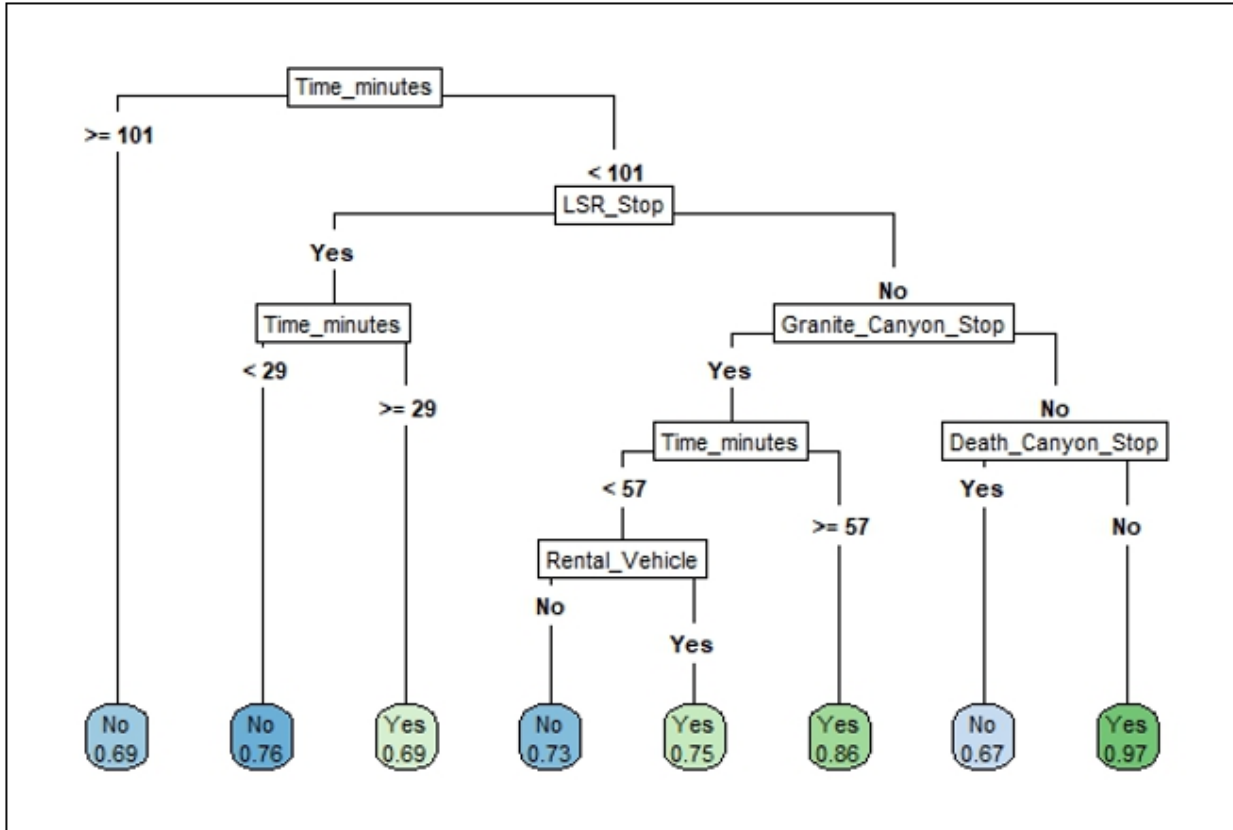


Figure 4-7 Decision Tree for Sawmill Ponds Stop as the Response Variable

Table 4-5 Confusion matrix for Sawmill Ponds model

		Did Vehicle Stop at Sawmill Ponds?	
		Predicted	
		No	Yes
Actual	No	40	12
	Yes	28	83
Accuracy		75%	
Precision		87%	
Recall/Sensitivity		75%	
Specificity		77%	

The Sawmill Ponds decision tree model consisted of seven nodes, where the time spent in the corridor was the parent node and the attractions of LSR, Granite Canyon, Death Canyon, and rental vehicle were its child nodes. The probabilities of stopping at Sawmill ponds are more

evenly distributed and appear to have a more significant relationship with other attractions and the amount of time spent in the MWC. However, the greatest predicted probability of 0.97 was observed when vehicles did not spend less than 101 minutes in MWC, did not stop at LSR, Granite Canyon and Death Canyon. This result indicates what is likely the typical behavior in MWC, which is that most visitors stop at Sawmill Ponds even after stopping at other attractions. The observations that show greater probabilities of stopping at Sawmill Ponds could be explained by the convenience and ease of access to the Sawmill Ponds overlook when traveling on the MWC.

The Sawmill Ponds decision tree model performance evaluation resulted in an accuracy of 75%, a precision of 87%, a recall of 75% and specificity of 77% with 28 false negatives and 12 false positives. The model similarly captures a different behavior than was observed in the Granite Canyon and Death Canyon models in that more vehicles are stopping, but a closer result to what was observed in the LSR model. Therefore, the model results in excellent accuracy in terms of correct classification at 75%, and the precision in classifying vehicles that will stop correctly is the highest out of the previous models at 87%. There is a 75% probability that the model will correctly identify a vehicle that stopped and a 79% probability that the model will correctly identify vehicles which did not stop. Therefore, out of the previously considered models, the Sawmill Ponds model provides the greatest precision in correctly identifying vehicles that will stop.

Overall the data used in this study likely resembles similar behaviors and patterns of use that occur in other national park settings, where some attractions are targeted by certain types of groups or visitors, and other attractions are more likely to be visited by the greater majority. This can be interpreted in the models as some of the models resulted in high specificity, or high

probability that vehicles classified as not stopping would not stop. A promising result, however, was observed in the attractions which saw a better distribution of visitor stopping vs. not-stopping. Although the model accuracy suffered, the model recall and model precision were improved resulting in what would be considered an ideal model. Therefore, future studies or enhancement of current models would be advised to ensure a sample set that contains a more uniform distribution of stopping and non-stopping events.

4.7 Discussion of Results

The decision tree analysis utilized in this paper highlights how some of the MWC attractions are interrelated in attracting visitors and influencing the probabilities that visitors stop. Higher numbers of vehicles that stopped were observed for both Sawmill Ponds and the LSR, and each consisted of six child nodes composed of attractions and time spent in the corridor. Granite Canyon had a favorable effect on increasing the predicted probability of stopping at Sawmill Ponds and LSR. This could be explained by the southern entry of visitors that stop at Granite Canyon and travel straight through MWC, as Granite Canyon is one of the first attractions followed by LSR and Sawmill Ponds.

An interesting finding was identifying the amount of time spent in the MWC and how that affected the predicted probability of a vehicle stopping at the attractions. A precise observation in the data and in general is that the longer a vehicle spent in the corridor, the higher probability that it stopped at one of the attractions. However, the inclusion of time spent in the corridor allows for identification of the thresholds where time is partitioned for the considered attractions. The Death Canyon decision tree model illustrates this datum where 42 minutes in the

corridor was an attribute in predicting if a vehicle stopped or did not stop at the attraction, making 42 minutes a possible threshold for Death Canyon. Finally, some considered explanatory variables were determined not to influence the probability of stopping. This was more evident in Death Canyon and Granite Canyon and suggested that those attractions are likely favored by a small proportion of visitors interested in spending a more considerable amount of time in MWC and likely participating in time-dependent recreational activities.

The use of a decision tree methodology provides a potential approach for understanding and predicting visitor behaviors at specific park attractions by evaluating probabilities of vehicles stopping along a scenic corridor. The strength of the methodology lies in the graphical output as well as easily evaluating the model performance. Some of the limitations to the model and in general decision tree approaches can be observed when greater interactions between variables are present and more complex relationships are required to be identified. This is evident when comparing the LSR and Sawmill Ponds models to the Death Canyon and Granite Canyon models that had fewer child nodes. Future application of decision tree analysis in national parks is recommended to narrow down predictor variables of interest to simplify the model and ensure that the model is not overly sensitive on the data used for training it.

The methodology presented illustrates how machine learning methods and GPS-based tracking data can assist in providing predicted stopping information, relationships between variables, and critical time thresholds spent at considered attractions. This can assist national park managers in understanding visitor behavior based on easy to identify characteristics. By overcoming cellular or wireless service constraints, the acquisition of GPS-based tracking data through smartphone strategies may become more accessible for national parks, thus making the

presented work in this study a prime example of what can be repeated through data analytics and machine learning approaches.

4.8 Management Impact

The findings provide GRTE managers with information about how visitors are likely to stop at certain attractions in the MWC. Managers can, in turn, provide specific attraction information to visitors accordingly. Additionally, understanding how attractions influence stopping at other locations in the MWC provides an opportunity for park managers to reinforce information to the visitors or provide unique messages to specific groups. For example, results showed that the Granite Canyon and Death Canyon attractions each identified a fewer number of visitors that were not influenced by stopping at other locations. This suggests that there is a small window of opportunity to reach a unique group of visitors interested in attractions like Granite Canyon or Death Canyon. Finally, the developed models allow park management to estimate the probabilities of the number of visitors at specific attractions if entry and exit monitoring strategies are implemented. This can assist in future planning efforts in terms of parking threshold development and informing incoming visitors of the likelihood of findings parking at key attractions.

4.9 Conclusion

This paper presented an approach to evaluating collected GPS data through a non-parametric classification scheme known as decision trees. This approach, although not new, is becoming more useful in the era of big data and data analytics. Its non-parametric characteristics allow for a more confident evaluation of variables that may have high multicollinearity issues often seen in related response variables in frequentist statistics. The methodology and procedure

are useful as GPS tracking data may become more readily available through advancements in technology and cellphone/smartphone devices. Thus, the study provides a good example and a glimpse of a type of analysis that is available for national parks to implement intelligent decision-making strategies.

Four decision tree models were developed utilizing a data set with 814 observations, split into a training dataset with 651 observations (80%) and a 163 observation (20%) testing data set. The model accuracy for the considered response variables of stopping at Death Canyon, Granite Canyon, LSR and Sawmill Ponds were determined to be 94%, 90%, 76%, and 75% respectively. The LSR and Sawmill Ponds decision trees were each composed of six child nodes that consisted of other MWC attractions and the time spent in the corridor. The Death Canyon and Granite Canyon decision trees each had three child nodes mainly comprised of the other MWC attractions. Overall it was determined that Death Canyon and Granite Canyon exhibited similar decision tree results, attracting a smaller proportion of visitors which spent more time in the corridor and likely were attracted for recreational activities. The LSR and Sawmill Ponds decision tree model showed a more even distribution dependent on other attractions in the MWC but also on time spent in MWC. Due to its tree structure, Sawmill Ponds was observed to likely capture the majority of visitors that travel in MWC as vehicles that spent less than 101 minutes in the corridor and did not stop at Granite Canyon or Death Canyon had a predicted probability of stopping of 0.97. These findings can assist park management and planning by estimating attraction levels relative to attraction capacities if monitoring techniques are implemented.

4.10 Applying Findings into an Agent-Based Model

Applying the findings discussed in this chapter to an ABM requires the consideration of various aspects. First is the initial proportion of vehicles that will stop at the considered attractions along the corridor as the first stop must be encoded and assigned to each agent. Similarly, as discussed in chapter 3 a random number generated between 0 – 1 must be assigned to each agent (vehicle), and a certain threshold will correlate to stopping at the considered attractions.

Considering multiple stops requires repeating the procedure where an additional random number is generated and labeled as a second stop. The stopping conditions from the second stop can be extracted from the results generated from the decision tree models.

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5 CHAPTER 5: A Bayesian and Agent-Based Model Approach to Evaluating Transportation Alternatives in a National Park Corridor

This chapter is adapted from Fuentes, A., Heaslip, K., D'Antonio, A. (*In Preparation*). A Bayesian Method and Agent-Based Model Approach to Evaluating a Transportation Corridor in a National Park. *Journal of Transport Geography*.

5.1 Introduction

The National Park Service (NPS) in the United States is challenged with a mission to preserve federal and private lands in their prevalent natural, cultural and ecological condition. Additionally, the NPS goals for the future include developing new meaning and value to parks which still consist of conservation and recreation, but also expand on education, research, and the sharing of knowledge (*NPS 2016a*). Achieving the NPS mission is becoming a more significant challenge as recreational visits have been increasing since 2013, (*NPS 2018*) and park managers are tasked with multiple objectives which include: fulfilling the NPS mission, ensuring park operations are adequate and providing visitors with sufficient information and guidance upon arrival. The NPS objective to expand on the learning and research occurring at the parks provides park managers an opportunity to take proactive measures to meet and fulfill the NPS mission.

In this paper, a discussion of a tool developed to evaluate an NPS transportation corridor is presented proactively. Proactive management, as opposed to reactive management, consists of

taking measures and actions in preparation for anticipated changes. In the NPS case regarding transportation operations, proactive strategies may include being familiar with growth trends of visitation levels and taking appropriate measures to ensure the NPS can be adequately prepared to handle such levels instead of reacting to them once those levels are reached. Thus, the tool was developed by referencing data collected from the Moose-Wilson Corridor (MWC) in Grand Teton National Park (GRTE). However, the tool could be adapted for use in other NPS settings. GRTE, as well as other national parks, have focused on developing comprehensive management strategies that fulfill the NPS mission while protecting resources and values. In August of 2016, GRTE released the “*Moose-Wilson Corridor Final Comprehensive Management Plan / Environmental Impact Statement*” which evaluates four action alternatives to be considered for implementation in the MWC ([NPS 2016b](#)). The preferred alternative consists of incorporating various operational measures and the introduction of a new entrance station/queueing facility. One of the critical operational measures includes limiting the number of vehicles in the MWC to 200 vehicles at any one time. Which although enforces the goal of protection and conservation of the NPS federal lands, it also creates a management challenge in terms of transportation operations and expectations to GRTE and its respective visitors.

Therefore, this paper discusses a tool developed for transportation system evaluation in a national park and does so by utilizing a Bayesian method analysis in combination with Agent-Based Modelling (ABM). The motivation for using a Bayesian method analysis along with agent-based modeling is twofold. First, Bayesian inference has been described as an approach where its use is suitable with little or large amounts of data ([Downey 2013](#)). Incorporating such an approach is appropriate in an era where data availability and acquisition is enhancing at a rapid rate. Thus, there is an opportunity to identify a starting point for a framework where past data

can be combined with more recent observations to generate informative posterior distributions for decision-making purposes.

Additionally, the posterior distribution can later become the prior distribution in future analysis, which ultimately enforces an incentive to continue to monitor and implement consistent data collection strategies. Second, the incorporation of an ABM approach provides a platform to model and simulate events of interest. The motivation for implementing an ABM approach in this study is to capture the variation of behaviors and interactions experienced in the unique setting of a national park. Recreational driving and unique site-specific events such as wildlife sightings and scenery viewing are challenging to model in traditional transportation modeling platforms that are geared to address urban and rural driving conditions and behaviors. Thus, ABM provides an avenue to model what is observed in the NPS setting directly. Additionally, a benefit to becoming familiar with ABM in an NPS setting is the flexibility in incorporating various events of interest on a single platform.

In this paper, the developed tool addresses the NPS planning process by adapting the transportation and movement of vehicles to the GRTE MWC's anticipated and desired operational changes. The rules in the ABM platform consist specifying the arrival rates of vehicles, the service times at the entrance gate, the desired destination of vehicles, the time spent at the destination and limiting the total number of vehicles in the MWC capacity to 200 vehicles as is specified in the MWC GRTE plan. Additionally, the tool provides a certain degree of control to the user in allowing the introduction of a wild-life interaction by generating user-specified delay at the desired location. In developing the tool, a base model of the MWC is provided for park staff, and furthermore provides an approach forecasting the time of day where the corridor would reach capacity. Reaching capacity of 200 vehicles is an event that triggers

mandatory additional management of the MWC (e.g., closing the corridor to new incoming vehicles) and overall effects the management strategies of GRTE. In the tool, rules enforcing observed events and actions were determined from collected data and coded to the vehicle agents in the ABM.

The collected transportation data includes vehicle arrival rates, service times, turning movement proportions to attractions and duration at attraction locations that were used to evaluate the corridor transportation system. The attractions in the MWC consists of: Poker Flats, Granite Canyon, the Laurence S. Rockefeller (LSR) Preserve, Death Canyon and Sawmill Ponds. The implementation of the tool provides information about the type of future impacts that can be anticipated with GRTE's preferred comprehensive management plan. The overall objective of this paper is to illustrate a novel approach to utilizing available data to evaluate management plans or test alternatives with the use of Bayesian methods and ABM. Expressly, the methods are incorporated into a tool that is implemented to answer a critical question which will allow park staff to better prepare for the anticipated changes to the corridor. The critical question that the tool answers is *“Given observed arrival, service and visitation levels to considered attractions. At what time of day, if any, will a 200-vehicle capacity be reached in the MWC?”*

The remainder of this paper is organized into the following sections. Section 2 provides a literature review of related work and methodologies implemented in this paper. Section 3 provides an overview of the data used in the development and testing of the methodology and tool. Section 4 discusses the methodologies implemented in the utilization of the tool. Section 5 provides the results obtained from the implementation of the tool on the MWC. Section 6 provides a discussion of the performed work and describes the management implications. Lastly, Section 7 provides a summary and concludes the paper.

5.2 Literature Review

The tool developed in this study consists of utilizing two methods that have been proven to be useful in the area of data analysis and simulation. Bayesian methodology is a well-known concept which utilizes Bayes theorem to generate informative posterior distributions and has recently seen an increase in use due to computational advancements. Similarly, ABM is a method that provides agency professionals and researchers a platform to evaluate flexible events and experiments of interest. Bayesian methods and ABM are proactive approaches that can be adapted into the NPS planning process and are capable of efficiently utilizing collected data to generate and test possible implementation alternatives with open source platforms.

Bayesian method is a term that can be used to describe the use or application of Bayesian inference. Bayesian inference is distinctive of the classical inference or statistics often referred to as frequentist statistics in that “it treats model parameters as random variables rather than as constants” (*Puza 2016*). This is more relevant in that assumption of normality must be met in frequentist statistics to be able to make inferences on results, whereas working directly with distributions in Bayesian statistics (*Cowles 2013*). Overall, the Bayesian method consists of using Bayes theorem to utilize a prior distribution (past and historical data) and a likelihood (current data) and determine a posterior distribution which contains a higher degree of confidence and information about an event of interest (*Cowles 2013; Downey 2013; Martin 2016; Puza 2016*). Although Bayesian inference is not a novel concept, recent advances in computation have increased the efficiency in solving Bayesian inference problems that often require Markov Chain Monte Carlo (MCMC) sampling techniques to estimate posterior

distributions (*Cowles 2013; Martin 2016*). Overall, one of the conventional approaches to summarizing the spread of the posterior distribution is defined through the Highest Posterior Density (HPD) interval which is commonly used at the 95% HPD or 98% HPD. Different from the frequentist confidence interval, the Bayesian HPD allows for the discussion about the probability of a parameter having some value (*Martin 2016*). Additionally, the forecasting capabilities of Bayesian methods have been identified in various efforts that include GIS related transportation safety studies (*Li et al. 2007; MacNab 2004; Miaou and Song 2005*).

Agent-Based Modelling (ABM) is a modeling technique that applies to many disciplines. Its use in transportation is substantial as it allows for the simulation of prevalent conditions while allowing for the testing and assessment of alternatives without modifying or altering the real-world environment. Various commercial software such as VISSIM, AIMSUN, and CORSIM among others are specialized for transportation simulations and require a thorough understanding of the input parameters to obtain dependable results. Much of the logic, decision-making rules and algorithms to urban vehicle behavior and vehicle maneuvering are encoded within the software. The difference in ABM is that one begins the modeling from scratch in an environment provided by the ABM platform which is not restricted to the consideration of only vehicles on a roadway network, but flexible enough to include agents of any type if appropriately described. The most widely used ABM platform is NetLogo, a free open source system authored by Uri Wilensky and developed at the Center for Connected Learning and Computer-Based Modeling (CCL) at Northwestern University. The author defines ABM as “a computational modeling paradigm that enables us to describe how any agent will behave” (*Wilensky and Rand 2015*). Working in NetLogo consists of providing rules to an environment of *patches* (cells/squares) and *turtles* (agents) that change over *ticks* (time). The *patches* represent a two-

dimensional grid that can be described as an x-coordinate and y-coordinate on a plane/graph where if desired the *patches* can be given specific instructions of how to behave, what actions to take as well as interactions with other *patches* and *turtles*. The *turtles* represent the agents that can interact with each other and with the *patches*. *Turtles* typically traverse or perform actions in the bounded *world* that represents the NetLogo simulation visual environment as *ticks* (time) advance. In general, the modification of the *patches*, *turtles*, and *ticks* provides a flexible modeling environment where any unit of measurement can be incorporated to an ABM simulation if the proper unit conversions are implemented (*Wilensky 1999b*). NetLogo has been successfully implemented to investigate transportation-related issues and phenomena. Various examples include the evaluation of remote working conditions or work from home initiatives on the environment (*Ge et al. 2018*) and the evaluation of travel behavior of fishermen in southern India with the introduction of cell phone information and communication technology (*Foss and Couclelis 2009*).

The NPS planning processes considers multiple aspects in order to ensure the NPS mission is maintained. Thus, the NPS planning process encompasses the implementation of Environmental Impact Statements to ensure future alternatives conserve federally managed lands. As it relates to GRTE, recent interest in the MWC has emerged due to natural changes in the GRTE since the NPS parkwide transportation planning effort outlined in 2007. Changes include increased visitation levels and overall traffic as well as the introduction of the LSR Preserve to GRTE jurisdiction, new wildlife species migrating in the MWC area, and greater awareness of archeological considerations in the region. Thus, GRTE took active measures to develop the “*Moose-Wilson Corridor Final Comprehensive Management Plan / Environmental Impact Statement*” with the overall objectives of establishing a “long-term vision and

comprehensive management strategies within the Moose-Wilson corridor to ensure the protection of significant national park resources and values” (NPS 2016b).

Overall four alternatives were considered in the “*Moose-Wilson Corridor Final Comprehensive Management Plan / Environmental Impact Statement*” which were identified as Alternatives A – D. The alternatives will be discussed in terms of their impact to the transportation operations in MWC. Alternative A consisted of a no-action approach which continued current operations without any future implementations and overall served as a base alternative to compare alternatives B – D against. Alternative B, consisted of restricting through traffic in either direction during peak use periods, where access would be constrained past the LSR Preserve, and speed limits would be advised at 20 mph. Alternative C was the NPS preferred alternative and consisted of limiting the number of vehicles in the corridor at any one time during peak periods, introducing queuing lanes to the north and south ends of the MWC corridor, consideration of a transit system in the future and 20 mph speed limit. Alternative D consisted of allowing access to the MWC through a reservation system, where visitors without a reservation would be accommodated on a first come first serve basis (NPS 2016b).

5.3 Data

The data was collected for the MWC which is geographically located in western Wyoming and is within the boundaries and under the jurisdiction of GRTE. The MWC transportation characteristics consist of a two-lane road with opposing flows of traffic that are approximately 7.1 miles in length. Speed limits varying between 25 mph - 35 mph depending on road surface type (asphalt paved/unpaved). Additionally, entrance to the park is controlled by the Granite Canyon Entrance station which is located just north-east of Teton Village, a popular

resort just outside the boundary of the GRTE. The Granite Canyon entrance station manages visitor entry to travelers in the north-east direction towards the GRTE Headquarters and the Craig Thomas Discovery and Visitor Center. The north-east section currently remains unmanaged for incoming visitors traveling south-west through the MWC. The MWC and its associated safety concerns and characteristics are described in detail in a road safety audit (RSA) completed by the Federal Highway Administration in 2013 (*Brinkly et al. 2014*).

The data referenced in this study was obtained from two sources collected during the 2013 and 2014 seasons in the MWC at GRTE. Video collection systems captured vehicle counts and volumes in the MWC. Data was collected where the Granite Canyon Entrance is presently located in the south-west portion of MWC. Similarly, data were collected in the northern portion of the MWC near Teton Park Road, where an anticipated entrance station/queueing facility is desired to be introduced according to GRTE's comprehensive management plan preferred the alternative. Through the video data collection, time of arrivals was referenced to estimate arrival rates and headway times collected at the Granite Canyon entrance station were used to infer service times.

Furthermore, a stratified random sample of GPS tracks obtained from MWC visitors was also utilized. The GPS tracks were collected during the same periods in the 2013 and 2014 seasons and provided detailed information regarding visitor travel patterns as well as proportions of visitors that would visit the various attractions of interest. A full description of the collected data is available in technical reports provided to GRTE by a team of student researchers from Utah State University and Penn State University (*Monz et al. 2014; Monz et al. 2015*).

The data of interest for this paper was the observed vehicle arrivals during peak hours. It was determined that August resulted in the largest observed arrival rates in the southern and northern

segments of the MWC. Furthermore, the arrival rates were broken down into 15-minute bins of observations from where the peak-periods were identified from 8:30 AM – 1:00 PM. In terms of video collection strategies, six total days of data collection were collected for the Granite Canyon entrance station and the Moose end location which consisted of August 4th (*Monday*), August 5th (*Tuesday*) and August 24th (*Sunday*) in 2013 and August 8th, (*Friday*), August 9th (*Saturday*) and August 10th (*Sunday*) in 2014. Figure 5-1 illustrates the average vehicle arrivals at each location from the observed data.

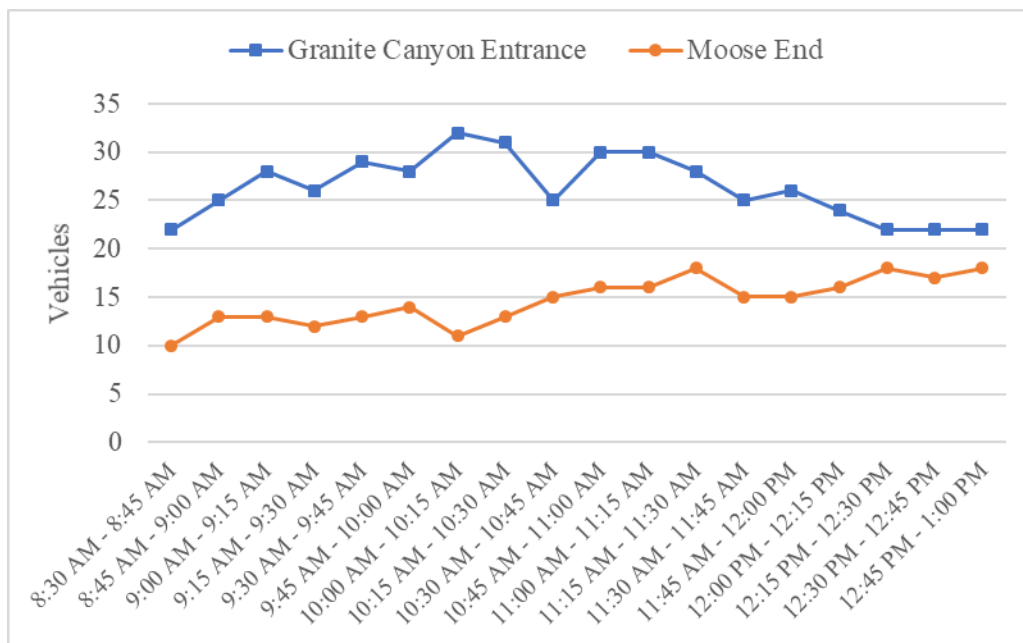


Figure 5-1 Arrival Rates at Granite Canyon Entrance Station and Moose End

Lastly, the GPS tracks were utilized to determine the proportion of vehicles which stopped at the considered attractions along the corridor. During the data collection period, a total of 547 GPS tracks were obtained in 2013 and 869 were obtained in 2014 totaling 1,416 tracks available. Of the 1,416 available tracks, 814 tracks were classified as stopping where stopping was defined as a vehicle not moving for more than 10 seconds. Therefore, the final proportions of vehicle movements are summarized in Table 5-1.

Table 5-1 GPS Tracks Data and Stopping Proportions

Vehicles Not Stopping		
Total		
602		
Vehicles Stopping		
Total	Stopped At	
814	30	Poker Flats
	78	Granite Canyon
	248	LSR
	59	Death Canyon
	399	Sawmill Ponds

5.4 Methodology

5.4.1 Bayesian Methods

The Bayesian inference procedure focused on referencing the observed arrival rates and inferred service times of the Granite Canyon entrance station to develop a posterior distribution and identify the 95% HPD region for that event. Overall three parameters of interest were sought to be obtained, the lower bound of the 95% HPD which is the 2.5% posterior quantile, the posterior mean and the higher bound of the 95% HPD which is the 97.5% posterior quantile.

Due to the analysis presented in this paper is the initial instance of performing Bayesian inference in the corridor, a common non-informative prior was utilized which is identified as Jeffreys prior throughout the Bayesian analysis. The Jeffrey’s prior is an alternative to using a uniform distribution prior, where an event is just as likely to occur or not occur, in other words, a uniform distribution where there is a 50% probability that an event occurs or does not occur. The Jefferey’s prior can be described as a beta distribution with alpha and beta parameters of 0.5 and has the advantage of being “invariant under transformations” (*Cowles 2013*) which enables flexibility if the transformation of parameters is required.

The Bayesian inference analysis was implemented in python and utilized the NumPy, SciPy, Pandas, Matplotlib, Seaborn and PyMC3 libraries where the PyMC3 library contains the Bayesian inference capabilities with MCMC sampling capabilities (*Martin 2016*). Thus, three Bayesian inference analysis was conducted for the Granite Canyon entrance station, the Moose end and the observed service rates to obtain the respective 2.5% posterior quantile, posterior mean and 97.5% posterior quantile of interest.

The Granite Canyon Entrance Station and the Moose entrance station each consisted 18 input observations representing a 15-minute bin period ranging from 8:30 AM and 1:00 PM and resulted in 18 posterior distributions each. The Bayesian inference for service time was conducted only for the service times during the August peak periods. Therefore, considering Jefferey's prior with the arrival rates from the Granite Canyon Entrance Station, the Moose end and one for the observed service times as the likelihood, Figure 5-2 and Figure 5-3 illustrate the 95% HPD region of the Granite Canyon Entrance Station and Moose end, respectively, while Table 5-2 illustrates the 95% HPD of the derived service times.

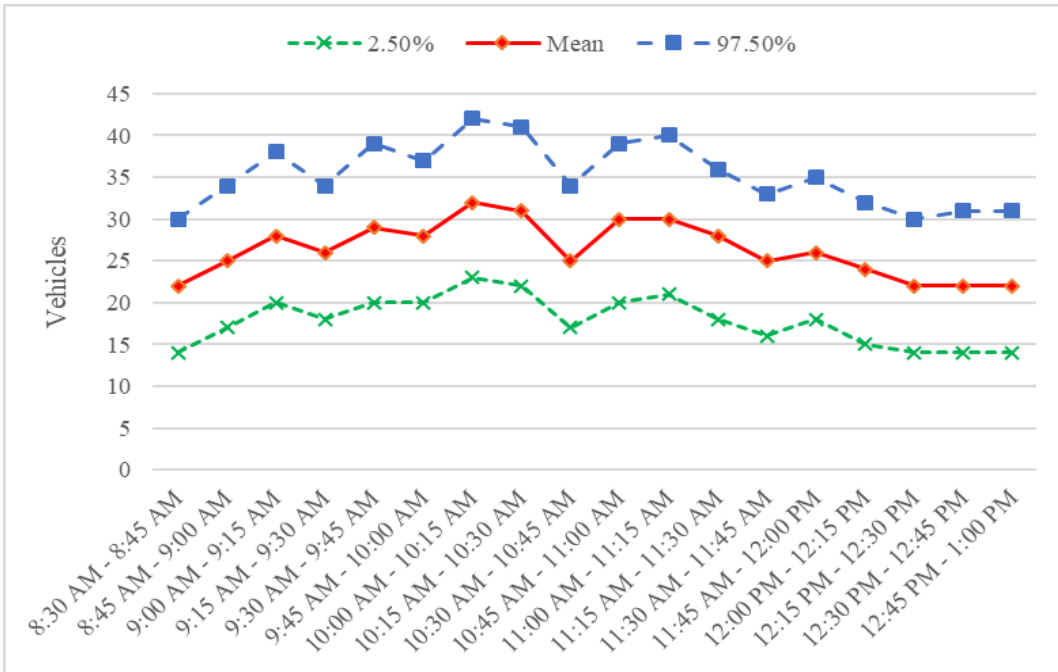


Figure 5-2 Bayesian Inference 95% HPD of August Peak Period at Granite Canyon

Entrance Station

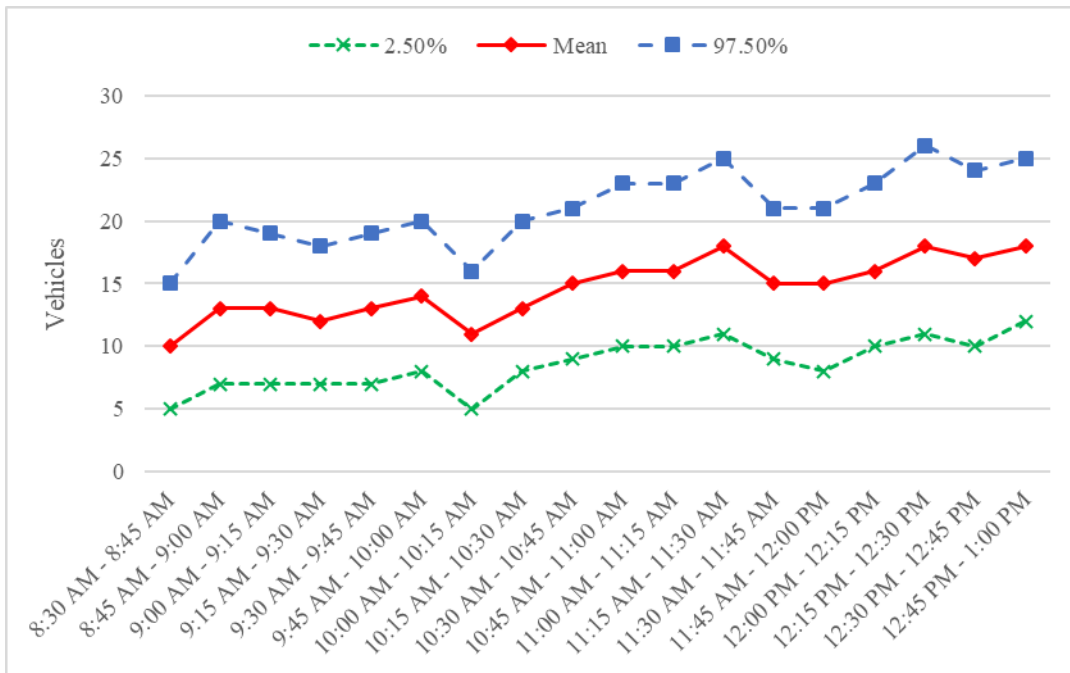


Figure 5-3 Bayesian Inference 95% HPD of August Peak Period at Moose End

Table 5-2 Bayesian Inference 95% HPD of August Peak Period Service Rate at Granite Canyon Entrance

Date	Service		
	2.50%	Mean	97.50%
8/4/2013	18	28	38
8/5/2013	18	28	38
8/24/2013	18	28	39
8/8/2014	18	27	37
8/9/2014	24	35	46
8/10/2014	20	30	40
Average Service Rate (veh/Sec)	19	29	40

4.2 Agent-Based Model

The ABM portion consisted of modeling the current MWC characteristics into a typical ABM environment where observed levels of vehicle arrivals and vehicle behaviors could be simulated. For this paper, the NetLogo ABM platform was utilized ([Wilensky 1999a](#)), and NetLogo's parameters were appropriately converted to represent the distance of the MWC, the placement of the entrance stations and the locations of where the considered attractions were about the MWC. The common units in NetLogo consist of *turtles*, *patches*, and *ticks* which represent the *agents*, *cells*, and *time* respectively. The agents were modeled as the vehicles traveling through the MWC, the cells represented the grid where the agents would travel through, and each was coded to be a 5 x 5-meter cell, and lastly, each *tick* or time unit was represented as 1 second. Thus, the total number of cells or *patches* in the NetLogo model resulted in 2,311 cells across the x-axis which represented 11,555 meters (7.18 miles) of the MWC. Similarly, the y-axis represented the distance needed to be traveled to reach each of the considered destinations and was maxed out by the LSR in the south-east at 100 *patches* (500 meters) and Death Canyon in the north-west at 400 *patches* (2,000 m).

Additional consideration of adapting NetLogo's units to represent the MWC consisted of labeling two "breeds" or types of agents referred to as northbound (NB-Vehs) and southbound vehicles (SB-Vehs). Each breed had specific instructions regarding their travel directions (North/South), speed and acceleration as well as awareness to slow down and not overlap or pass another agent on representing a car-following situation. In this study, the car-following rules implemented more closely resemble Pipe's model which is modeled after California Vehicle Code and keeps a minimum vehicle length distance from the following vehicle and the lead vehicle (*Elefteriadou 2014*). The network consisted of a two-lane corridor representing the main road of the MWC, and two-lane roads that reach the considered attractions of Poker Flats, Granite Canyon, LSR, Death Canyon and Sawmill Mill Ponds. Table 5-3 summarizes the assumed parameters and distances assuming the origin of the x-coordinates starts 200 meters before arriving at the Granite Canyon entrance station and the y-coordinates are the distance from the MWC. Figure 5-4 summarizes the MWC Network as it was modeled in NetLogo. In Figure 5-4 the Moose end entrance station can be modified by the user, in the experiments conducted for this paper, the Moose end entrance station was set at 300 meters away from the "End of Network" or the northernmost intersection where MWC intersects with Teton Park Rd.

Table 5-3 Description of NetLogo Parameters and MWC Network Characteristics in NetLogo

NetLogo Parameters	
One tick	1 second
One patch	5-m x 5-m cell
One turtle	NB - Vehicle Agent SB - Vehicle Agent
MWC Network Characteristics	
Granite Entrance Station	X = 40 (200 m), Y = 100 (Datum)
Poker Flats	X = 153 (765 m), Y = 97 (15 m)
Granite Canyon	X = 367 (1,835 m), Y = 106 (30 m)
LSR	X = 1083 (5,415 m), Y = 0 (500 m)
Death Canyon	X = 1299 (6,495 m), Y = 500 (2,500 m)
Sawmill Ponds	X = 1881 (9,405 m), Y = 97 (15 m)
Moose Entrance Station	X = 2011 (10,055 m), Y = 100 (Datum)

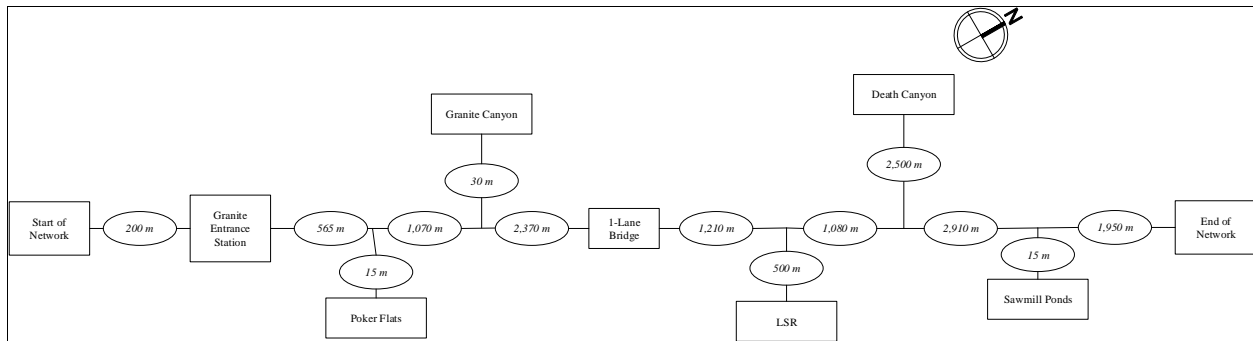


Figure 5-4 MWC Network Representation in NetLogo

Furthermore, the rules integrated for the agents to follow consisted of moving from the start of the Network towards the End of Network if they were an NB-Vehicle and from End of Network to Start of Network if they were an SB-Vehicle. Both NB and SB vehicles were to follow the vehicle in front of them. Additionally, each vehicle was assigned a random number between 0 – 1 upon passing their respective entrance station which determined what attraction they would be stopping at. Table 5-4 illustrates how these numbers were distributed based on GPS tracking data obtained during the data collection process.

Table 5-4 Stopping Rules for NB-Agents & SB-Agents in MWC NetLogo Model

Vehicles Not Stopping	
Random Number Range	Action
0.0000 - 0.3910	Thru
0.3911 - 0.4300	U-Turn
Total Proportion	43%
Vehicles Stopping	
Random Number Range	Stopping At
0.4301 - 0.4511	Poker Flats
0.4512 - 0.5058	Granite Canyon
0.5059 - 0.6791	LSR
0.6792 - 0.7207	Death Canyon
0.7208 - 1.0000	Sawmill Ponds
Total Proportion	57%

Furthermore, referencing the GPS tracks, the time spent at each location was estimated based on total time spent in the corridor. Observed values from the data collection were input into the ABM model in terms of mean and standard deviation of time spent at each attraction. In NetLogo, additional flexibility was provided for future users in that a user input box for the mean and standard deviation for time spent at an attraction was allowed to be easily modified. Thus, using NetLogo’s capabilities, a random number was drawn from a normal distribution with constraints based on the specified mean and standard deviation that would determine how long an agent would spend at any one attraction. Therefore, the process of an agent to visit a site consisted of the following steps. Upon, passing through the entrance station a random number pulled from a normal distribution and between 0 and one was assigned to each agent, that number would determine their stopping destination based on the Table 4 specifications. The duration of time spent at the attraction was determined from a random number generated by NetLogo bounded by user-specified inputs of mean and standard deviation. The mean and standard deviation used for this study consisted of values observed during the data collection process.

Figure 5-5 illustrates a screenshot of the NetLogo ABM model, where the user can modify various operational parameters of the model. The arrival rates can be modified to allow for vehicles arrivals in a deterministic fashion or through a Poisson process. Similarly, the entrance stations are encoded into a patch behavior where a color designation can serve vehicles in a deterministic or Poisson fashion. Furthermore, the monitoring includes queuing levels at the Granite Canyon Entrance Station, the Moose End entrance station, the number of vehicles at the considered attractions of Poker Flats, Granite Canyon, LSR, Death Canyon and Sawmill Mill Ponds and the total number of vehicles in the MWC as time progressed are also monitored.

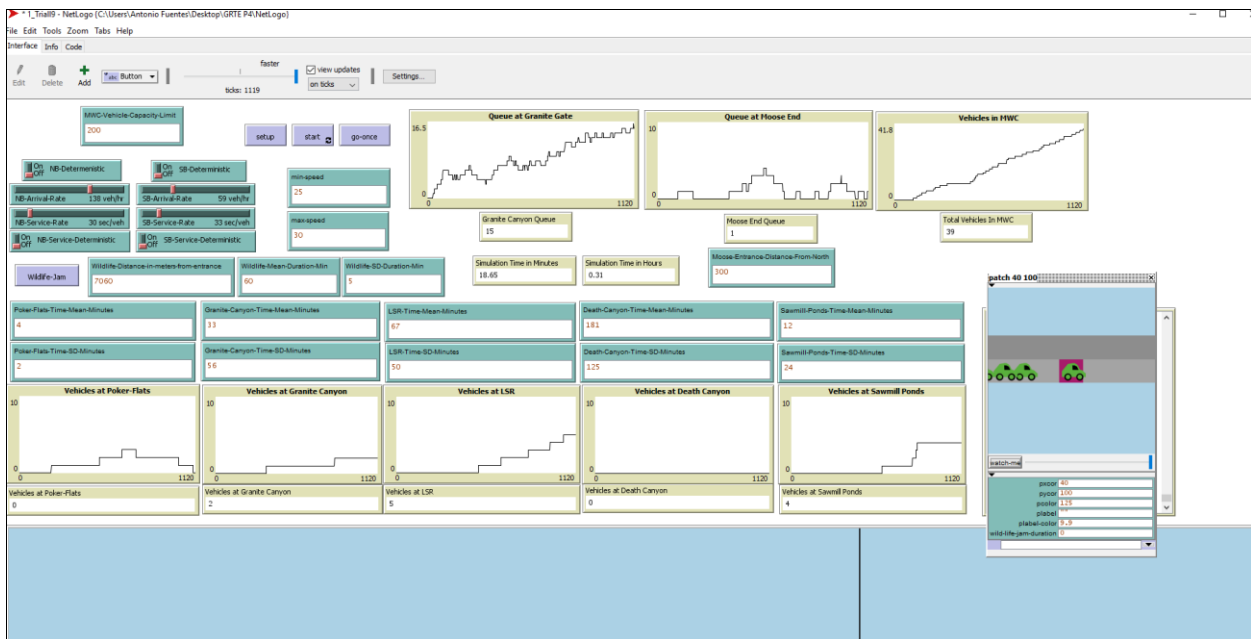


Figure 5-5 The MWC Modeled in NetLogo

An additional feature which is included in the NetLogo ABM Model is the consideration of wildlife jams to the corridor. This feature is provided to the user in terms of providing control to where in terms of location a wild-life jam may occur, and for how long it will last. The vehicle agents are instructed to react to the jam by stopping and thus introducing a delay to the corridor. Including this characteristic highlights the flexibility available in ABM to modeling the unique

scenario in the MWC that involves frequent interaction with wildlife and the natural scenery. Although in this study the wildlife jam feature was not included in the data collection process, its discussion is vital for two reasons. First, it highlights the appropriateness of the use for ABM to be used to evaluate different NPS corridors where additional unique events may be modeled. Secondly, it provides a path for future research that could incorporate a specific plan to address the sensitivity wildlife jams may have to vehicle travel in the MWC.

5.5 Results

5.5.1 Agent-Based Model

The resulting 95% HPD values determined from the Bayesian analysis were used as the primary inputs in the ABM simulation for a time period from 8:15 AM – 1:00 PM for a total of 17,100 seconds (*ticks*) where the first 15 minutes were allotted to a warm-up period of vehicles already in the corridor. Three cases were evaluated and referred to as the 2.5% posterior quantile case, the posterior mean case and the 97.5% posterior quantile case. A total of 20 simulations per case for three cases were executed resulting in available data for 60 simulations where an identified random seed value was maintained for repeatability measures. Figure 5-6 illustrates the results from the simulations of the average number of vehicles arriving at the Granite Canyon entrance gate considering the previously identified and discussed parameters. From the simulation results, as expected the 2.5% posterior quantile results had favorable results, vehicle arrival levels remained below ten vehicles until approximately 10:30 AM, at which point 10 vehicles could be anticipated to be constantly arriving within the monitoring area until 1:00 PM. The posterior mean and the 97.5% posterior quantile resulted in each having similar behaviors

and vehicle arrival levels under the considered conditions similarly beginning to peak at the 10:30 AM time of day. Similarities can likely be attributed to the considered arrival and service rates converging under the coded conditions which include a specified monitoring distance of vehicle arrivals. Additionally, the change in slope shortly after 11:00 AM can be attributed to the 200-vehicle capacity being reached within the corridor and vehicles being unable to enter until others leave after the 11:00 AM time of day.

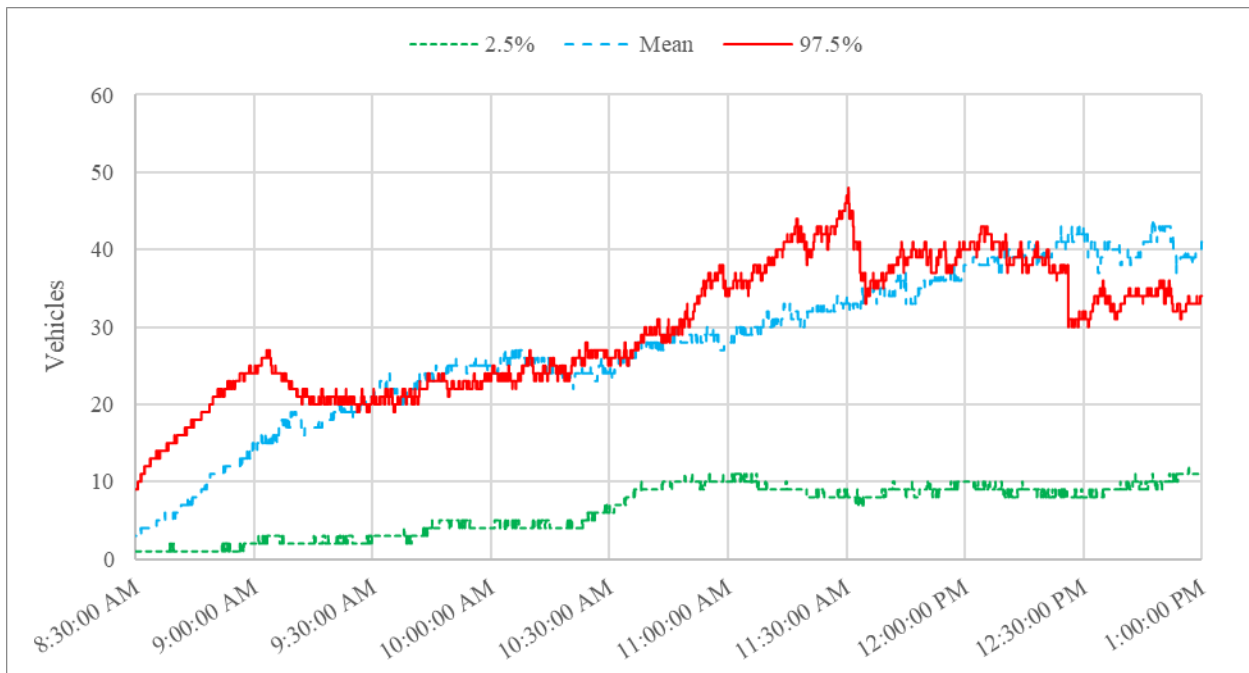


Figure 5-6 Average Vehicles Arriving at the Granite Canyon Entrance in MWC from NetLogo Simulations

Figure 5-7 illustrates the results from the simulations of the average number of vehicles arriving at the Moose end future entrance gate considering the previously described parameters. There is a clearer distinction between the 2.5% posterior quantile, posterior mean and 97.5% posterior quantile. Overall the system arrival levels begin to accumulate starting at 11:00 AM considering the posterior mean conditions and as early as 10:00 AM under 97.5% posterior

quantile conditions. The sudden peaks in the results can be explained by the MWC reaching 200 vehicles in the system and blocking access to the arriving vehicles.

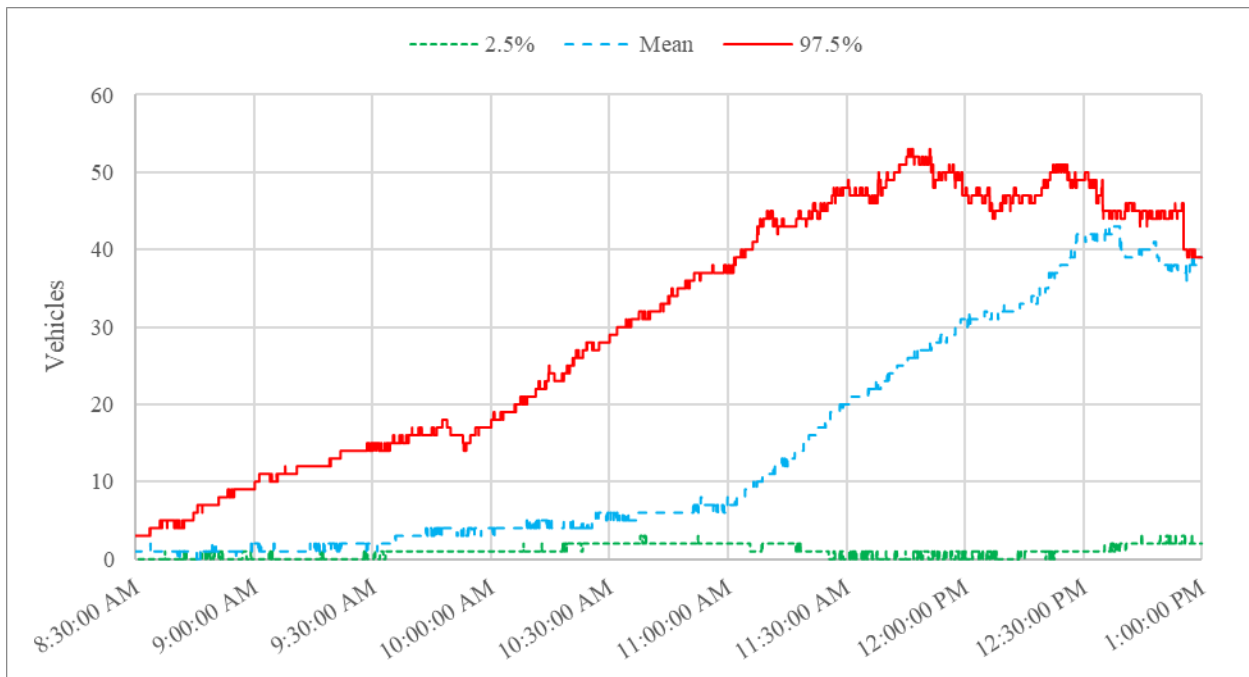


Figure 5-7 Average Vehicle Arrivals in the Moose End of MWC from NetLogo Simulations

Figure 5-8 illustrates the results from the simulations of the average number of vehicles expected to be in the Poker Flats attraction of MWC. Overall Poker Flats was the least interesting attraction in terms of observed visitors stopping due to the low proportion of visitors stopping during the data collection process. Overall, considering the modeled parameters the Poker Flats attraction resulted in approximately one vehicle being present throughout the 8:30 AM – 1:00 PM time frame.

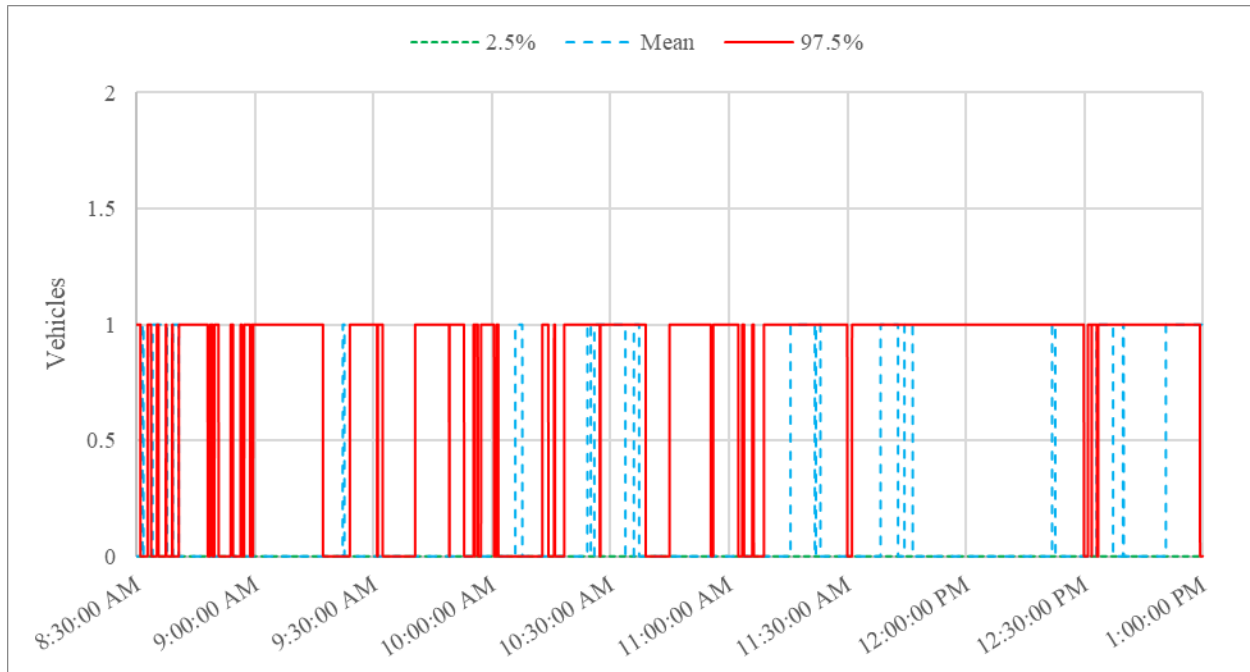


Figure 5-8 Average Number of Vehicles at Poker Flats Identified in the MWC from NetLogo Simulations

Figure 5-9 illustrates the results from the simulations of the average number of vehicles expected to be at the Granite Canyon attraction of MWC. The maximum number of vehicles at the Granite Canyon attraction under the 2.5% posterior quantile, posterior mean and 97.5% posterior quantile were estimated to be five vehicles, eight vehicles, and 14 vehicles respectively. This finding is important as GRTE park managers can anticipate the number of vehicles to be at the Granite Canyon trailhead under observed conditions and can help identify how the visitor time that is spent in Granite Canyon affects the remainder of the corridor.

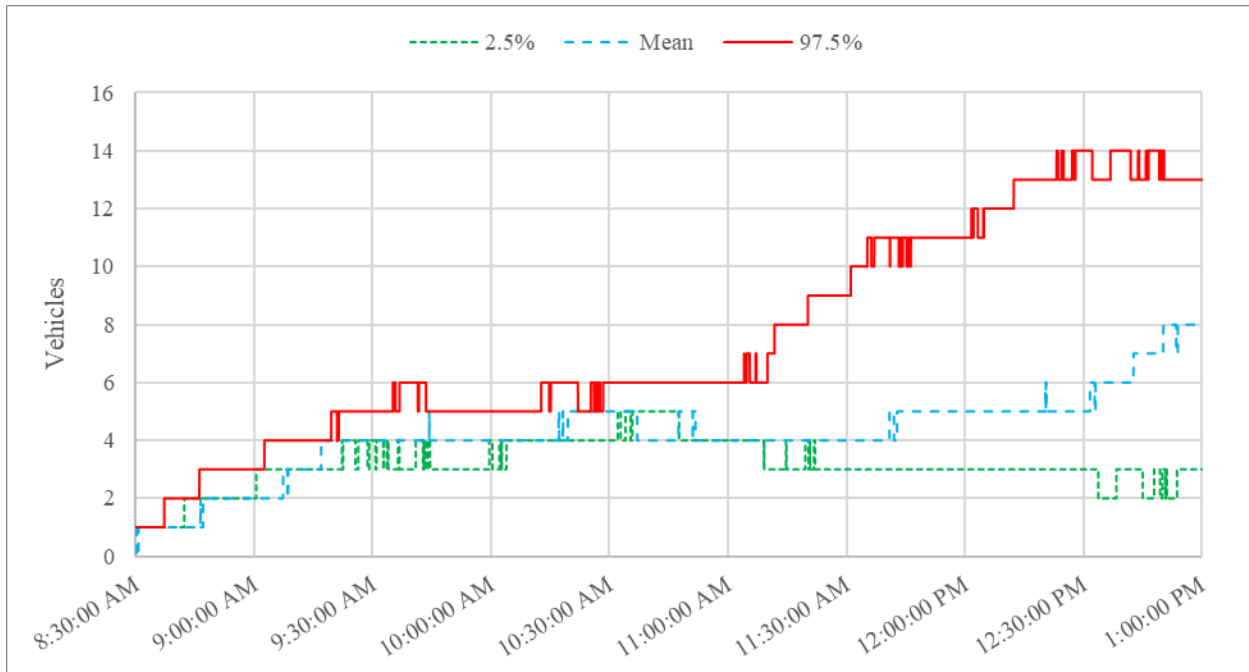


Figure 5-9 Average Number of Vehicles at Granite Canyon Identified in the MWC from NetLogo Simulations

Figure 5-10 illustrates the results from the simulations of the average number of vehicles expected to be in the LSR attraction of MWC. The maximum number of vehicles at the LSR Preserve attraction under the 2.5% posterior quantile, posterior mean and 97.5% posterior quantile were estimated to be 19 vehicles, 31 vehicles, and 45 vehicles respectively. Estimation of vehicles at the LSR attraction is important to the GRTE park managers as there is a parking capacity limit of 54 designated spaces, thus under the high arrival rates of the 97.5% posterior quantile and observed stopping proportions; it is reassuring to observe levels below the 54-parking space limit.

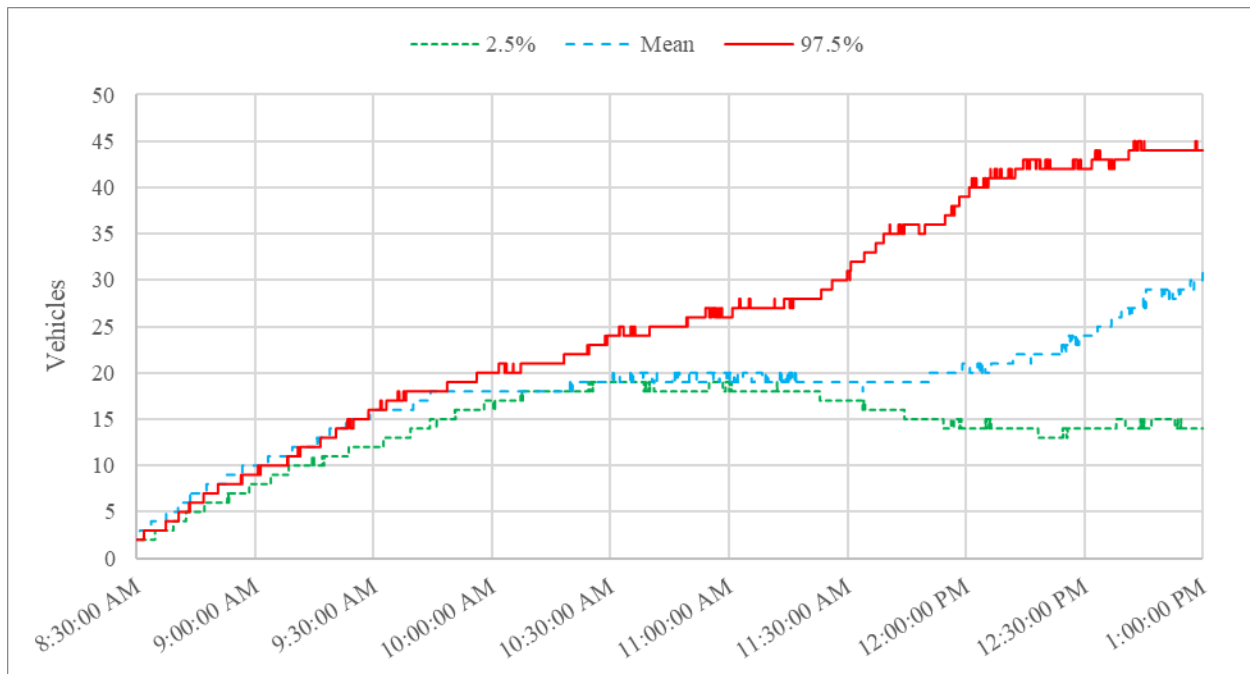


Figure 5-10 Average Number of Vehicles at LSR Identified in the MWC from NetLogo Simulations

Figure 5-11 illustrates the results from the simulations of the average number of vehicles expected to be in the Death Canyon attraction of the MWC. The maximum number of vehicles at the Death Canyon attraction under the 2.5% posterior quantile, the posterior mean and 97.5% posterior quantile were estimated to be 13 vehicles, 21 vehicles, and 35 vehicles respectively. The behavior observed in Death Canyon can be described as an incrementing step graph due to the long durations that were observed at the attraction. From the simulated results, there is little evidence that vehicles visiting the Death Canyon attraction and intending to spend time there would leave the MWC during the considered 8:30 AM – 1:00 PM timeframe.

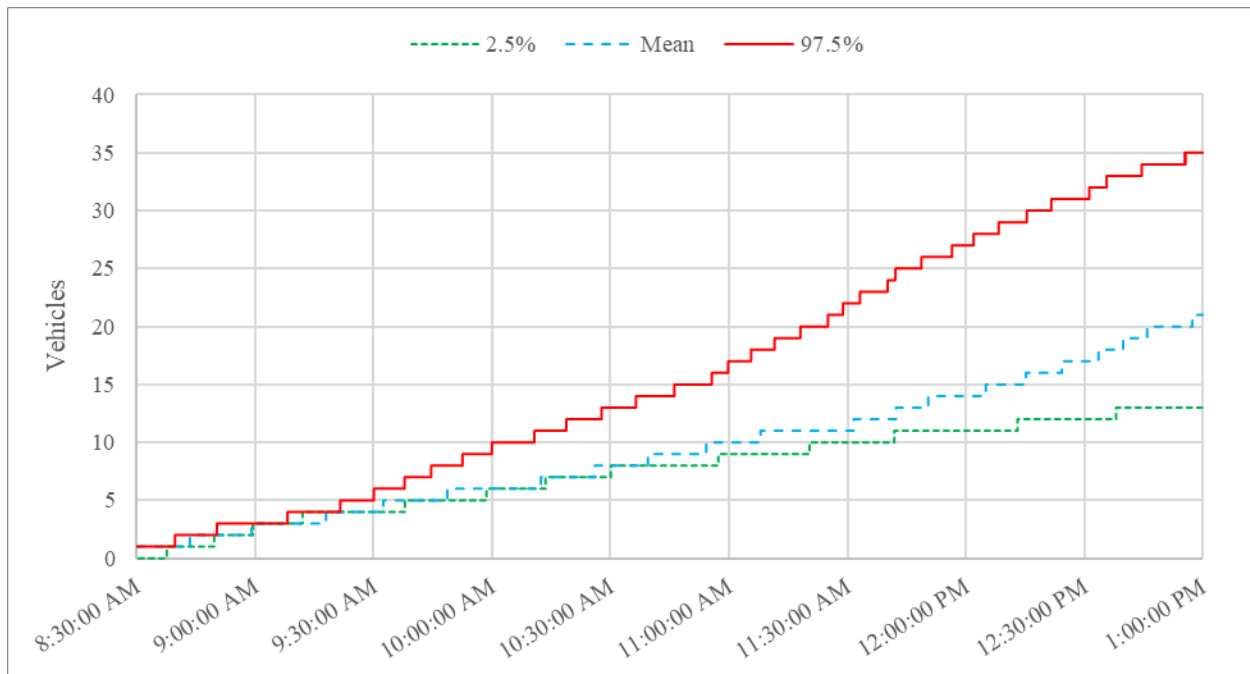


Figure 5-11 Average Number of Vehicles at Death Canyon Identified in the MWC from NetLogo Simulations

Figure 5-12 illustrates the results from the simulations of the average number of vehicles expected to be at the Sawmill Ponds attraction of MWC. The maximum number of vehicles at the Sawmill Ponds attraction under the 2.5% posterior quantile, the posterior mean and 97.5% posterior quantile were estimated to be 17 vehicles, 20 vehicles, and 31 vehicles respectively. Sawmill Ponds was observed to be one of the most visited attractions by the MWC visitors, likely due to its ease of access and the opportunity it provides the visitors to connect with MWC’s natural environment. The main take away from the results is that the estimated fluctuation of a visitor at Sawmill Ponds is greater than any other attractions. Number of vehicles at Sawmill Ponds appear to reach and remain at a steady state between 10:00 AM – 11:30 AM. Relative to park management, this attraction would likely benefit the most from operational parking strategies to optimize flow in and out of the Sawmill Ponds attraction.

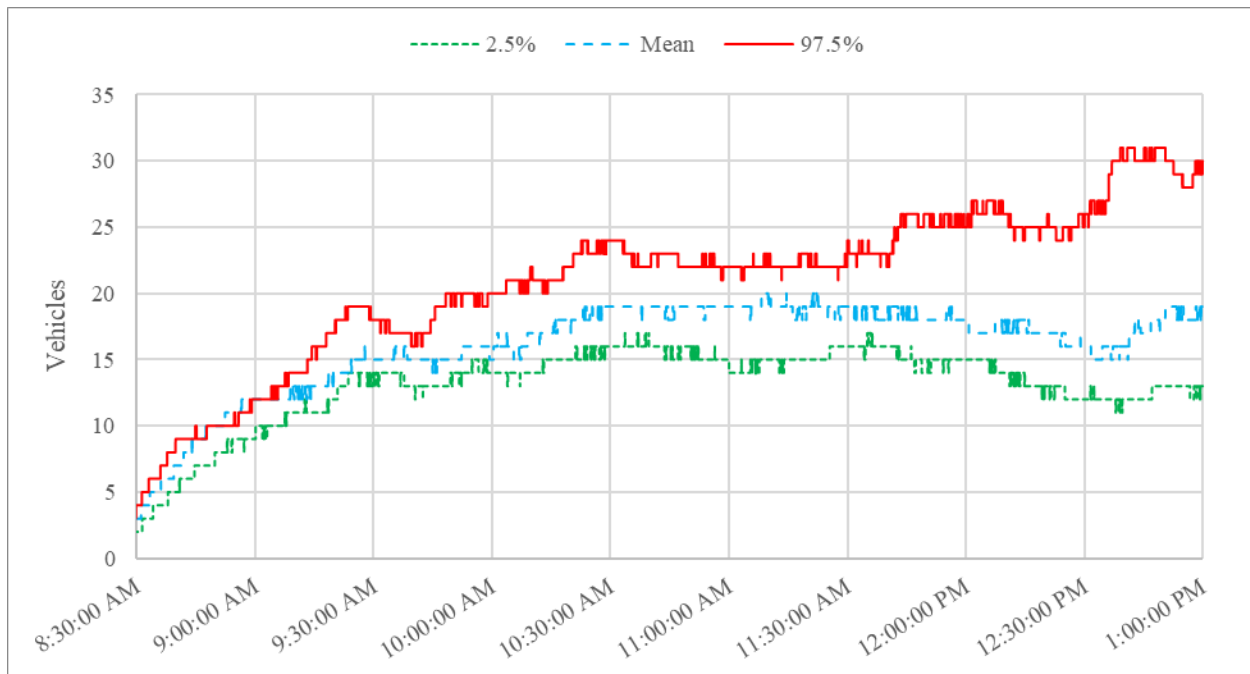


Figure 5-12 Average Number of Vehicles at Sawmill Ponds Identified in the MWC from NetLogo Simulations

Thus, to summarize and provide perspective from the model results of the attraction visitation levels and the approach used to estimate the MWC capacity, the results are summarized in Table 5. Additionally, Table 5 below illustrates the anticipated number of vehicles that were referenced in the comprehensive management plan (*NPS 2016b*) to estimate the 200 vehicle capacity derived out of the maximum person capacity at three out of the five attractions. Thus, it can be observed that the model results for the 97.5% posterior quantile more closely resemble the numbers used in the development of the MWC 200 vehicle capacity. The results provide confidence that the current 200 vehicle capacity is well designed to account for the conservative values tested in the model, and below the posterior mean values which were observed in the field.

**Table 5-5 Comparison of Comprehensive Management Plan Vehicles at Attractions to
NetLogo Model Results**

	Estimated by GRTE	NetLogo Model Results		
		2.50%	Mean	97.50%
Poker Flats	-	0	1	1
Granite Canyon	17	5	8	14
LSR	44	19	31	45
Death Canyon	80	13	21	35
Sawmill Ponds	-	17	20	31
Total Vehicles at Attractions	141	54	81	126
Available Vehicle Capacity in MWC	59	146	119	74

Lastly, Figure 5-13 illustrates the average of the total number of vehicles that were observed in the MWC simulations. Keeping in mind that vehicles were not allowed to enter the MWC after 200 vehicles were within the MWC boundaries between the Granite Canyon entrance and the Moose end entrance. The results show that under the 2.5% posterior quantile conditions the posterior mean conditions the number of vehicles in the MWC resulted in approximately 170 vehicles and the 200-vehicle capacity was not reached. However, the 170-vehicle mark was reached just before 11:00 AM under the posterior mean conditions and around 10:15 AM under the 97.5% posterior conditions. The results illustrated in Figure 5-13 address a critical issue in GRTE’s comprehensive management plan and overall raises awareness about the time of day the MWC will reach 200 vehicles when considering the visitor stops along the MWC attractions and the duration of time spent at each location. Overall, the most significant impact this finding has is informing at what time of day capacity will be reached or if capacity will be reached at all in the MWC. Along the same lines, it provides GRTE management with a tool with predictive capabilities to testing more up to date arrival rates and determine if capacity is

reached. More importantly, it helps park management to prepare to consider if, when and where additional management strategies are needed given visitor levels and travel patterns.

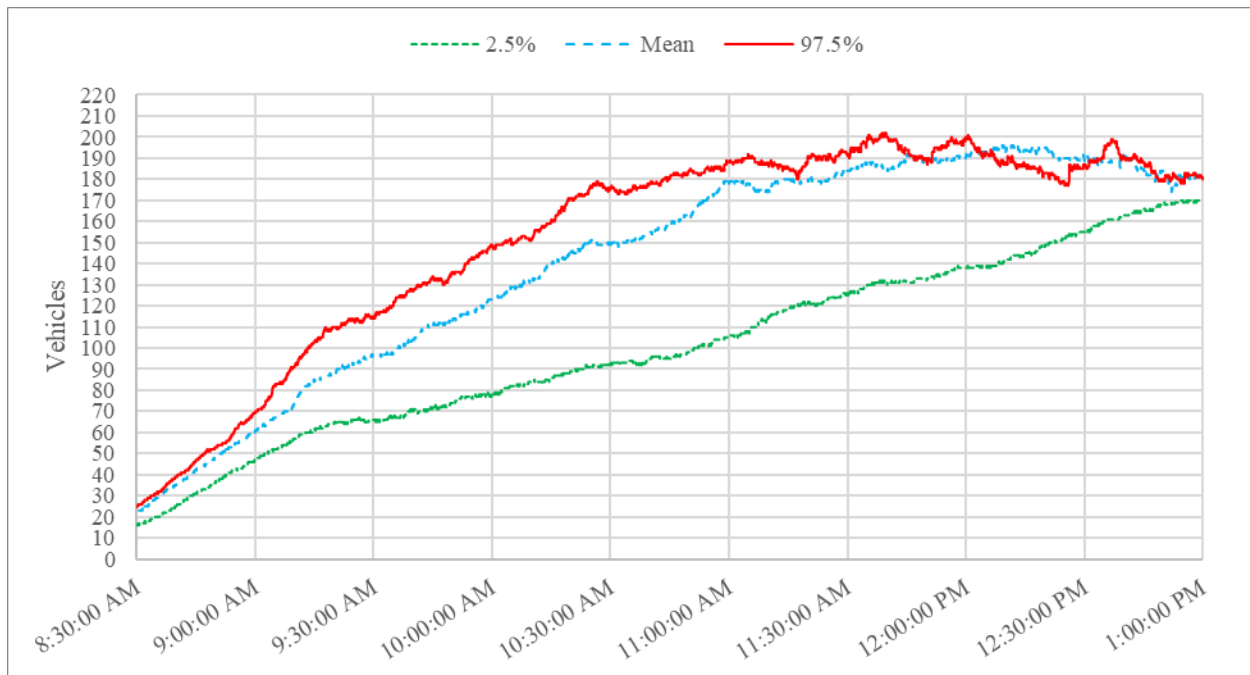


Figure 5-13 Average Total number of Vehicles in the MWC Corridor Identified in the MWC from NetLogo Simulations

5.2 Verification

Verification methods consisted of evaluating the time spent within the MWC. The GPS tracks provided information for vehicles that *did not* stop while traveling through the MWC. Similarly, information was provided for vehicles that *did* stop and the time spent in the MWC. Therefore, Table 5-6 illustrates a comparison of the time spent in the MWC from the collected GPS vehicles compared to the considered NetLogo simulations. It must be noted that because Death Canyon saw such a significant amount of time spent in the attraction, the vehicles did not exist within the considered time from of 8:30 AM – 1:00 PM and thus, information was not available for direct comparison. The percent difference is calculated for each case against the

GPS collected data, overall there was adequate consistency between the NetLogo simulations and the percent difference did not exceed 50% for the cases which were able to be compared.

Table 5-6 NetLogo Time in MWC Comparison to GPS Data

	GPS (Minutes)	NetLogo (Minutes)			% Difference: GPS & Netlogo Minutes		
		2.50%	Mean	97.50%	2.50%	Mean	97.50%
Thru (No Stop)	22	21.85	14.78	14.42	0.68	39.26	41.63
Poker Flats	26	33.17	24.26	23.38	24.24	6.92	10.61
Granite Canyon	55	63.08	47.67	81.89	13.69	14.28	39.29
LSR	89	85.81	91.58	74.62	3.65	2.86	17.58
Death Canyon	203
Sawmill Ponds	34	39.64	40.90	40.44	15.32	18.42	17.30
Average % Difference					11.51	16.35	25.28

5.3 ANOVA

A final analysis consisted of performing an analysis of variance (ANOVA) followed by a Tukey’s posthoc test comparing the time of day expected for 200 vehicles to be reached in the MWC. Figure 5-14 illustrates a boxplot representing the time of day 200 vehicles were reached from each simulation case, while Table 5-6 and Table 5-8 represent the ANOVA results and post-hoc Tukey analysis.

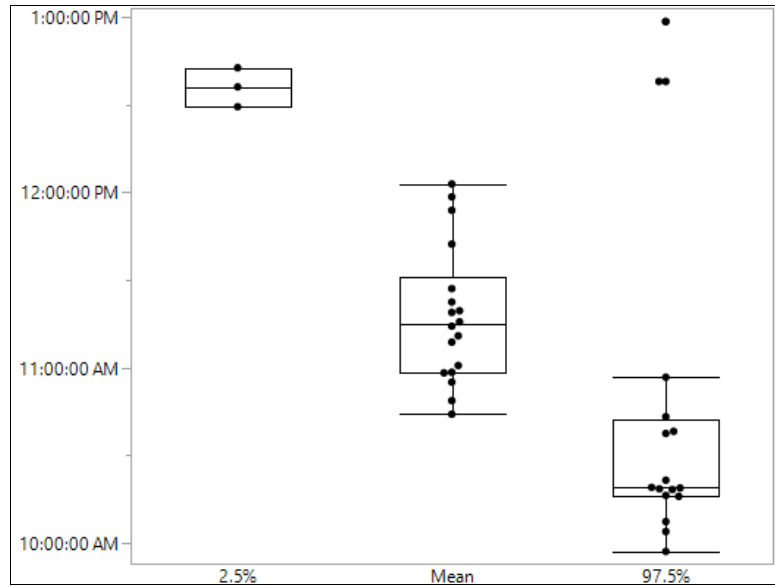


Figure 5-14 Box-Plots of the Time the MWC Capacity of 200 Vehicles was Reached

Table 5-7 ANOVA Table of Time of Day to Reach 200 Vehicles in the MWC

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	133119600	66559800	12.4923
Error	34	181153791	5328052.7	Prob > F
C. Total	36	314273390		<.0001

Table 5-8 Tukey's HSD Post-Hoc Test

Level		Least Sq Mean	
2.5%	A		45359.667
Mean		B	40668.556
97.5%		C	38435.688
Levels not connected by the same letter are significantly different.			

Therefore, it was determined that the null hypothesis is rejected and that the considered 2.5% posterior quantile, the posterior mean and 97.5% posterior quantile have significantly different time of day values were the anticipated number of vehicles will reach 200 in the MWC. Performance of Tukey's honestly significant difference (HSD) post-hoc test further illustrates that each case considered is significantly different from each other when evaluating the data with

frequentists approaches. Overall, Figure 5-14 provides further information about the variation of when the 200-vehicle capacity can be reached. Under the 2.5% posterior quantile, the observations which saw a 200-vehicle capacity were approximately after or around the 12:30 PM threshold. The posterior mean saw a greater spread in times ranging from approximately 10:45 AM to just after 12:00 PM. Lastly, the 97.5% posterior quantile conditions saw capacity being reached shortly before 10:00 AM until 11:00 AM.

Thus, the ANOVA results previously presented describe the time of day bounds that the 200-vehicle capacity may be reached in the MWC. With monitoring strategies in place to capture vehicle arrival rates and entrance station service times, park managers could estimate the potential time of day capacity is reached in the MWC. Favorable conditions of low arrival rates and quick service times would correlate to the 2.5% posterior quantile results and reaching capacity at approximately 12:30 PM. Alternatively, conservative conditions of high arrival rates and slower service times would correlate to the 97.5% quantile results and reaching capacity as early as 10:00 AM. This information can provide park managers threshold levels of when additional staff may be required to handle mitigation strategies at the MWC entrance station locations given that monitoring is in place.

5.6 Discussion and Conclusions

A tool which consisted of implementing Bayesian methods and ABM was developed in order to evaluate an NPS transportation corridor. The tool capitalizes on carrying out analytical methods which are becoming prevalent in the field of transportation engineering when data collection and data analysis is required. In addition to presenting the tool, the paper provides a

methodology capable of being adapted to other NP locations to answer similar management plan questions or test various strategies with open-source resources.

The tool was utilized in the GRTE to evaluate the preferred alternative of the “*Moose-Wilson Corridor Final Comprehensive Management Plan / Environmental Impact Statement.*” The tool was able to use available data to estimate critical aspects of interest to GRTE such as the time a 200-vehicle capacity limit is reached in the MWC. The presented work demonstrates an approach to investigating possible scenarios in the MWC utilizing advanced data analytics procedures and ABM modeling platforms. The data analytics portion uses collected previously collected data from 2013 and 2014 that serves as the likelihood for Bayesian method evaluation. Bayesian inference is not a new concept but is being used utilized more frequently due to advances in computation power and the overall push in data acquisition that has emerged in recent years. Results from the Bayesian analysis consisted of identifying a 95% HPD region that could be used as bounds to input into an ABM representing the MWC.

The purpose of the ABM was to represent the MWC and examine the anticipated changes proposed by the comprehensive management plan. Utilizing the 95% HPD region output from the Bayesian method analysis provided bounds which would define the parameter inputs for three different cases when comparing simulations, the three cases where: the 2.5% posterior quantile, the posterior mean and the 97.5% posterior quantile. Furthermore, observed proportions and stopping durations from GPS tracks allowed for the determining and assigning rules to agents about which attractions they would stop at and how long they would be stopped along the MWC.

Thus, the described procedure was implemented to estimate the operations within the MWC at GRTE when limiting the capacity of MWC to 200 vehicles. The Bayesian inference

provides a 95% HPD region which increases the overall confidence that the considered parameters being utilized in the ABM are what would be observed in real time. The NetLogo ABM provides a platform to simulate transportation events in the MWC. However, the overall capabilities of events that can be simulated by the NetLogo ABM are not limited to only transportation events and can be modified and adapted to include additional events common in an NPS setting such as interaction with wildlife or other ecological phenomena.

Overall considering the time of day when 200 vehicles were reached under the 2.5% posterior quantile values resulted in an average time of day of 12:26 PM. The posterior mean case resulted in greater instances where the 200-vehicle capacity was reached in the MWC with the average expected time to be at 11:13 AM considering observed values. Lastly the higher 97.5% posterior quantile which consisted of, the greater vehicle arrival rates and longer service times resulted in stressed operational measures at the entrance stations. Overall the 200-vehicle capacity was observed to be reached at an average time of 10:40 AM under the 97.5% posterior quantile conditions.

An ANOVA analysis comparing the means between the considered cases of the 2.5% posterior quantile, the posterior mean and 97.5% posterior quantile found that each case was statistically significantly different from each other. However, because the 95% HPD was used to determine the bounds of the simulation parameters the probability obtained from the performed analysis that 200 vehicles are reached between 10:40 AM and 12:26 PM is 0.95.

6.1 Management Impacts

The most significant impact the tool provides to the NPS parks interested in performing a proactive evaluation is demonstrated through the evaluation of the MWC in GRTE. The tool provides GRTE management; a platform where the current preferred management plan can be

tested. The point of most significant concern for GRTE and other parks of the NPS is the objective of conservation and preservation and limiting visitor capacity as proposed with the 200-vehicle limit in GRTE is a direct way to address and ensure the NPS mission. By having access to estimates of possible time of day periods where the 200-vehicle capacity is reached, GRTE can better prepare to handle possible queuing levels at the entry points to the MWC or also enforce time spent at the attractions of Poker Flats, Granite Canyon, the LSR Preserve, Death Canyon and Sawmill Ponds. Under the observed posterior mean conditions, were the largest vehicle arrivals for August were input into the ABM, the time of day where 200 vehicles were reached was approximately 11:13 AM.

The power of ABM should not be overlooked as it is a flexible platform was the NPS can evaluate future planning endeavors that are not only limited to transportation-related efforts. Similarly, the flexibility to change input parameters such as arrival rates and service rates are likely to change over time especially since visitation levels have been observed to be increasing over time and the common seasonal effects.

5.7 Conclusions

In conclusion, a tool was developed to evaluate an NPS transportation corridor. The tool consisted of capitalizing on the use of advanced analytical methods that consist of Bayesian methodology and ABM. To illustrate the tools capabilities data from the MWC at GRTE was modeled in the NetLogo ABM platform to evaluate the preferred alternative of the “*Moose-Wilson Corridor Final Comprehensive Management Plan / Environmental Impact Statement.*” The alternative consisted of limiting the number of vehicles in the corridor at any one time during peak periods, introducing queuing lanes to the north and south ends of the MWC corridor,

consideration of a transit system in the future and 20 mph speed limits. Currently, a 200-vehicle capacity is expected to be enforced where access will not be allowed in the MWC during this period.

The data used was collected during the 2013 and 2014 seasons at GRTE and consisted of vehicle arrival rates at the Granite Canyon Entrance Station and the Moose end of the MWC. Additionally, a stratified random sample of GPS tracks of visitors traversing the MWC corridor and visiting key attractions of interest which include Poker Flats, Granite Canyon, the LSR Preserve, Death Canyon and Sawmill Ponds.

A Bayesian method approach was applied to the arrival rate data and service time data to obtain a 95% HPD region that would serve as bounds for values to be modeled in an ABM. The evaluation focused on peak periods observed during the data collection process which were observed during August of 2013 and August of 2014, where the morning periods of 8:30 AM – 1:00 PM were explicitly evaluated. Additionally, the obtained GPS tracks allowed for the estimation of stopping proportions of vehicles traveling through the MWC and the time spent at each attraction.

The tool is an ABM that was modeled on the NetLogo platform and was modified to represent the MWC starting from the Granite Canyon Entrance station and ending at the Moose End intersection with Teton Park road. Key aspects of the NetLogo ABM allow for the user to modify variables of interest such as the arrival rates and service rates of the Granite Canyon Entrance Station and the Moose end as well as specifying whether they arrive or provide service in a deterministic or Poisson fashion. Similarly, the time spent at each location is a parameter that can be altered by a user by inputting the average time spent at the location and the standard

deviation. Currently, the observed values are encoded into the model and were also the values utilized to complete the evaluation for this paper.

The arrival rates and service rates obtained from the Bayesian method approach were used to run 20 simulations for three cases of the 95% HPD region. Three cases considered were the 2.5% posterior quantile, the posterior mean and the 97.5% posterior quantile that resulted in a total of 60 simulation data sets for a simulation period ranging from 8:30 AM – 1:00 PM. Data consisted of monitoring results in the developed tool which also monitored the vehicles (agents) traveling through the MWC and stopping at assigned attractions for a specified amount of time.

It was estimated that under the 2.5% posterior quantile values which were the parameter values of low arrival rate and faster service time, the average estimated time of day for the MWC to reach the 200-vehicle capacity was 12:26 PM. Under the posterior mean values which were the observed average values of vehicle arrivals and service times, the average estimated time of day for the MWC to reach the 200-vehicle capacity was 11:13 AM. Lastly, under the 97.5% posterior quantile parameter values which were the conservative values of high arrival rates and slower service times, the estimated time of day for the MWC to reach the 200-vehicle capacity was 10:40 AM.

Therefore, the tool provides a useful resource for NPS managers to evaluate current and future management strategies. For this paper, the tool was tested with data from the GRTE, MWC and the respective MWC management plan. The evaluation focused on estimating a unique unknown event of reaching a 200-vehicle capacity in the MWC during peak visitation periods with the use of Bayesian methods and ABM. The time range to reaching capacity was estimated considering a 95% HPD region of observed conditions and visiting proportions and durations. The developed tool provided the NPS with a valuable resource and methodological

approach to future management plans as illustrated in the GRTE MWC management plan. Additionally, the ABM platform developed can be updated and reused to capture any changes within the MWC as well as integrating additional behaviors from visitors or wildlife in the area.

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6 Chapter 6: Conclusion

In conclusion, in this dissertation, various methods illustrate how available data can be extended to determine prevalent transportation system operational performance, prepare and plan for future transportation system changes and illustrate methodologies, tools, and approaches to evaluating a unique transportation system. Under the same scope, proactive support methodologies and support tools were discussed and serve to illustrate approaches of transportation system operation management for National Park Service managers as well as non-traditional agency professionals. This was accomplished by focusing on the Moose-Wilson Corridor located in Grand Teton National Park.

This was accomplished in Chapter 2, through evaluation of the queuing levels of performance through the Little's Law methodology and simulation. The methodology implemented serves as a useful tool for National Park Service entrance stations and is not only restricted to vehicle arrivals. Also, in Chapter 2, similar methodologies were implemented to evaluate a considered entrance station at the northern end of the Moose-Wilson Corridor and provide guidance and recommendations to the anticipated number of queued vehicles and the consideration of distance and placement from the nearest intersection to avoid queue spillback.

In Chapter 3, traditional queuing methodologies and the application of Little's law provided a thorough evaluation of the parking queuing levels at the Laurance S. Rockefeller Preserve (LSR) in the Moose-Wilson Corridor. Consideration of arrival rates throughout the day and the approximate duration spent parked allowed for the estimate of queuing measures of performance for the parking area. With such information, recommendations regarding parking time limit enforcement when certain thresholds are reached were provided.

In Chapter 4, the use of GPS tracks collected along the Moose-Wilson Corridor was utilized to implement a non-parametric machine learning strategy to attempt to identify stopping attractions along the corridor. The machine learning strategy consisted of a decision tree approach and considered the time spent in the corridor as well as other stops made throughout the corridor and provided predictions about the probability that a visitor would stop in a certain attraction. Findings from this study allowed park managers to glimpse into implementing new decision-making strategies and easily observe trends of visitor attractions while being able to inform incoming visitors of the probability of finding parking spaces if monitoring is implemented.

Lastly, in Chapter 5 the use of arrival rates, service times and GPS tracks collected from the Moose-Wilson Corridor were used to generate a Bayesian inference 95% Highest Posterior Density bounds that would later be input as parameters to an Agent-Based Model. The overall objective of Chapter 5 is to investigate the transportation operations of the Moose-Wilson Corridor considering the preferred management plan that limits vehicle capacity to 200-vehicles. Findings from this study determined three average times of day results that correlate to three values within the 95% Highest Posterior Density (2.5% posterior quantile, posterior mean, 97.5% posterior quantile) of observed arrival and service rates at the Moose-Wilson Corridor. Overall guidance and anticipated time of day were approximations provided for reaching the 200-vehicle capacity limit in the Moose-Wilson Corridor under the future preferred management plan operations.

Overall each chapter served to provide information relevant to park management at GRTE and illustrates a detailed process to evaluate a National Park corridor. A big component of this work is the implementation of ABM to model a National Park transportation system.

ABM provides a platform for evaluating the unique transportation characteristics observed in a National Park. Additionally, it inherently contains the flexibility to include multiple interactions that may be observed in a non-urban environment. One that stands out is the interaction that visitors have with the wildlife present in a National Park and the desire to spend time observing the natural scenery of the environment. Such behavior is capable of being considered in an ABM after overcoming the learning curve of the ABM platform. Additionally, regarding the presented study, because the transportation operations are dependent on the unique events of GRTE, many commercial tools are not readily adapted to address the unique conditions that involve considering wildlife or sightseeing scenarios.