RESEARCH & DEVELOPMENT

Investigation of Wait Time Technology for the Ferry System

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16. Abstract

The North Carolina Department of Transportation (NCDOT) Ferry Division operates vessels on seven routes along the eastern coast of North Carolina. The routes serve diverse populations, ranging from routes with substantial tourist/visitor customers to routes with primarily daily commuters. Similar to traffic signals on a road network, queuing and waiting are unavoidable at ferry terminals, and wait times and queue lengths are important considerations of customers. However, measuring and communicating wait times and queues is not simple and not currently available to NCDOT ferry customers. The NCDOT Ferry Division would like to implement technology that can reliably measure and track wait times. The objectives of this project was to 1) review and test options for measuring wait times and 2) recommend the implementation of a system to measure and track wait times for installation at ferry terminals.

This research conducted a systematic review of the state-of-the-art of technologies that can be used for measuring wait times. Summary tables were developed with information that can be used by the Ferry Division and other NCDOT staff to understand the advantages and disadvantages of various technologies. Then, this research tested the feasibility of applying BlueTooth and License Plate Recognition (LPR) technologies to track vehicles and estimate waiting times at ferry terminals. Based on a series of tests, this research revealed that the LPR technology has a sampling rate of 84.2 percent; the average capture rate and read rate are 84.3 percent and 87 percent, respectively. The match rate was found to be 79.4 percent, which is significantly higher than the match rate of Bluetooth devices (9 percent). Thus, the LPR technology was recommended for waiting time estimation. Based on field data collected at the busiest ferry terminal in North Carolina, this research found that travelers tended to experience long waiting times during midweek days, particularly during the mid-day period. Additionally, the demand was found to be the primary factor for wait times during the mid-day peak period, and travelers' arrival time in terms of proximity to the scheduled ferry departure time was recognized as the key factor for waiting time during early morning and later evening non-peak periods.

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EXECUTIVE SUMMARY

The North Carolina Department of Transportation (NCDOT) Ferry Division operates vessels on seven routes along the eastern coast of North Carolina. The routes serve diverse populations, ranging from routes with substantial tourist/visitor customers to routes with primarily daily commuters. Similar to traffic signals on a road network, queuing and waiting are unavoidable at ferry terminals, and wait times and queue lengths are important considerations of customers. However, measuring and communicating wait times and queues is not simple and not currently available to NCDOT ferry customers.

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This research conducted a systematic review of the state-of-the-art of technologies that can be used for measuring wait times. Summary tables were developed with information that can be used by the Ferry Division and other NCDOT staff to understand the advantages and disadvantages of various technologies. Then, this research tested the feasibility of applying BlueTooth and License Plate Recognition (LPR) technologies to track vehicles and estimate waiting times at ferry terminals. Based on a series of tests, this research revealed that the LPR technology has a sampling rate of 84.2 percent; the average capture rate and read rate are 84.3 percent and 87 percent, respectively. The match rate was found to be 79.4 percent, which is significantly higher than the match rate of Bluetooth devices (9 percent). Thus, the LPR technology was recommended for waiting time estimation. Based on field data collected at the busiest ferry terminal in North Carolina, this research found that travelers tended to experience long waiting times during midweek days, particularly during the mid-day period. Additionally, the demand was found to be the primary factor for wait times during the mid-day peak period, and travelers' arrival time in terms of proximity to the scheduled ferry departure time was recognized as the key factor for waiting time during early morning and later evening non-peak periods.

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INTRODUCTION

The North Carolina Department of Transportation (NCDOT) Ferry Division operates 21 ferry vessels on seven routes along the eastern coast of North Carolina, as shown in Figure 1. The service carries over 200 trips daily and transports approximately 850,000 vehicles and two million passengers a year, making it the second largest state-run ferry system in the United States (NCDOT, 2021). The ferry system provides a critical transportation link for NC residents for their daily commuters to work, school, shopping, recreation, etc., and enables visitors to access to tourism destinations or even just experience the ride. Moreover, in some island locations, the ferries are the only connection to local communities. The system saves more than $1.5 million annually transportation-related costs by reducing travel time and vehicle miles traveled (VMT) on alternative routes (NCGA, 2017). Additionally, the system brings considerable economic benefits to local residents and their businesses. According to a study conducted by Bert et al. (2020), the system supports a total of 5,860 jobs with $217.3 million in labor income and $735.2 million in total economic output.

Figure 1 NCDOT Ferry Route Map

As with many road transportation systems, queuing is an unavoidable phenomenon at ferry terminals. Vehicles must wait for vessels to arrive before they can commence their crossing. After the ferry reaches capacity, it departs the terminal according to its scheduled sailing time. So, unless demand is low, vehicles must wait until the next ferry arrives to board. Moreover, when demand exceeds capacity, customers may have to wait two or more sailings. In practice, wait time is an important consideration of customers, and a critical challenge for the operation of ferry transport is how to manage customer expectations and ensure that there is a clear sense of when people will be able to board and how long they must wait. Sometimes, customers choose to abandon their trips because the wait is too long, especially for tourists. This tends to result in a loss of economic benefits. For instance, it was found that during the 2015 tourist peak season, 2.2% of vehicles waiting at the Hatteras ferry terminal abandoned their trip to Ocracoke Island, which equated to approximately $375,000 in lost revenue for Ocracoke businesses (Findley et al., 2018). The reason for the abandoned ferry rides (or customer dissatisfaction of the ferry service) was partially attributed to the fear of uncertainty. Waiting, in the absence of information, tended to engender a sense of powerlessness, whereas situational information, such as advance notices of the expected waiting time or the maximum waiting time, helped alleviate anxiety, thus improving user satisfaction (Maister, 1985).

Therefore, the NCDOT Ferry Division would like to implement technology that would measure, track, and communicate wait times, since an accurate estimation of wait time would be valuable for the effective operation of the ferry system (Díez-Gutiérrez and Tørset, 2019). Moreover, waiting time is a key performance assessment criterion for capital improvement projects, such as ferry service frequency changes or ferry replacement projects (Andersen and Tørset, 2019).

This project will seek to understand, test, and recommendation implementable technology solutions that will reliably measure and track wait times. The objectives of this research are: 1) review and test options for measuring wait times and 2) recommend the implementation of a system to measure and track wait times for installation at ferry terminals.

LITERATURE REVIEW

Queuing is an unavoidable part of ferry services. The vessels must arrive and depart, so cars and trucks must wait until the next ferry arrives to board. Moreover, when demand exceeds capacity (in terms of vehicles served per hour), customers must wait one or more sailings. The challenge, therefore, is how to manage customer expectations and ensure that there is a clear sense of when people will be able to board and how long they must wait.

Small (2012) indicates, as many others have before, like Houston et al. (1998), that the perceived cost of waiting is much higher than that of traveling. Hanssen, Jørgensen, and Larsen (2019) affirm this in the context of the Norwegian ferry services. Moreover, Maister (2005) suggests that waits which are uncertain and unexplained have even higher perceived costs. Hence, Dziekan and Kottenhoff (2007) and Fan, Guthrie, and Levinson (2015) suggest that providing real time information about wait times very much helps improve the quality of the waiting experience.

Given today's telecommunication (IT) technology, as with Smart Trek, described by Kamnitzer and Bro (1999) in the context of the Puget Sound area (where there are many ferry services), it should be possible to convey pertinent information to the customers about how long they will have to wait. The questions are 1) what data should be collected (e.g., video, Bluetooth, cell-phone), 2) how these data should be used to generate useful information, and 3) how the information should be presented (through the web, historical information, existing social media platforms, etc.).

This literature review examines what has been tried before in terms of: 1) data collection strategies that have been explored, 2) data processing ideas that have been developed, and 3) dissemination strategies that have been tried.

Existing Frontier

The most useful studies regarding data collection, processing, and results dissemination are shown in Table 1. Some have examined just one of these topics; others have examined the first two. Only a few have examined all three.

Table 1 Investigations of Data Collection, Analysis, and Results Communication

<table>
<tr><th>Data Collection</th><th>Analysis</th><th>Results Communication</th></tr>
<tr><td>Takaba et al. (1991)</td><td>Houston et al (1998)</td><td>Kamnitzer and Bro (1999)</td></tr>
<tr><td>Higashikubo et al. (1996)</td><td>Zhang et al. (2017)</td><td>Dziekan and Kottenhoff (2006)</td></tr>
<tr><td>Sabean and Jones (2008)</td><td>Rashidi et al. (2018)</td><td>Kelley (2018)</td></tr>
<tr><td>Sen et al. (2012)</td><td>Zhao et al. (2019)</td><td>Alaska Marine Highway System (2019)</td></tr>
<tr><td>Barone (2019)</td><td></td><td>Barone (2019)</td></tr>
<tr><td>BATS (2019)</td><td></td><td>British Columbia Ferry Services (2019)</td></tr>
<tr><td>Minea and Dumitescu (2019)</td><td></td><td>Cape May-Lewes Ferry (2019)</td></tr>
<tr><td>Security Sales and Integration (2019)</td><td></td><td>Houston TranStar (2019)</td></tr>
<tr><td>DataFromSky (2020)</td><td></td><td>Washington State Ferries (2020)</td></tr>
<tr><td>Washington State Ferries (2020)</td><td></td><td></td></tr>
<tr><td colspan="2">Ban, Hao, and Sun (2011)</td><td></td></tr>
<tr><td colspan="2">Mucsi, Khan, and Ahmadi (2011)</td><td></td></tr>
<tr><td colspan="2">Cheng et al. (2012)</td><td></td></tr>
<tr><td colspan="2">Hao and Ban (2015)</td><td></td></tr>
<tr><td colspan="2">Zhu et al. (2015)</td><td></td></tr>
<tr><td colspan="2">Shu et al. (2016)</td><td></td></tr>
<tr><td colspan="2">Findley et al. (2018)</td><td></td></tr>
<tr><td colspan="2">Andersen and Tørset (2019)</td><td></td></tr>
<tr><td colspan="2">Zhao et al. (2019)</td><td></td></tr>
<tr><td colspan="3">Ceder and Varghese (2011)</td></tr>
<tr><td colspan="3">Lerner and Sawyer (2015)</td></tr>
<tr><td colspan="3">Cullen et al. (2018)</td></tr>
<tr><td colspan="3">Reimer (2019)</td></tr>
<tr><td colspan="3">Washington State DOT (2019)</td></tr>
</table>

Data Collection

Data collection is the activity that collects the inputs upon which the wait time assessments are based. Sabean and Jones (2008) suggest there are three main ways to collect the data: 1) wayside sensors; 2) vehicle (device) sensors; and 3) vehicle (device) trackers. Each of these is discussed below. Technologies used in wait time studies to monitor queue length include radar, loop detectors, video surveillance, radio frequency identification (RFID), Bluetooth, WiFi, and GPS.

Wayside Sensors

These devices are installed to detect the presence of vehicles. Table 2 describes the most common technologies used and their advantages and disadvantages. A common example is a detection system that uses loop detectors. These devices cannot identify individual vehicles; they only can sense that a vehicle is present or that it has passed by. Communication with the vehicles is not involved. However, by monitoring vehicle actuations at several locations, cumulative arrivals and departures can be estimated; and thereby wait times. Ban et al. (2011) and Hao and Ban (2015) provide examples for signalized intersections (which may seem different, but the flow is still interrupted, as with ferries). For example, if a loop detector is installed upstream of the back of queue and another at the discharge point, the cumulative arrivals and departures can be tracked. The difference between these at any point in time is the number of vehicles in the queue assuming vehicles cannot enter or leave the queue at intermediate points. If one further assumes that FIFO is maintained (that is, the first one in is the first one out), then the total time in the system can be calculated for each vehicle, and a rolling average wait time can be computed.

Another good example is a system that uses video cameras. Bastion (2019) describes an applicable technology. If properly mounted, the camera can measure the length of the queue directly, by identifying the location of the back of queue in the image. It may be possible to count the vehicles directly (some video processing systems can complete this task) or the number can be estimated based on the observed length and an assumed average vehicle length. Higashikubo et al. (1996) provide an early example; Zhu et al. (2015) present a more recent example. Discharges at the front of queue (which are likely to be visible in the video image) provide an estimate of cumulative departures and cumulative arrivals can be imputed based on the changes in queue length distance. DataFromSky (2020) is an example of a technology that can be employed for this task. As with the loop detector example, the resulting estimates of cumulative arrivals and departures can be used to estimate the wait time. These data can also be used off-line to assess system performance, as in computing diurnal trends in the average time in queue, the average time in system, and the distribution of wait times. There are other wayside sensor options; one that makes use of state-of-the-art digital instrumentation is the Kyun Queue, as described by Sen et al. (2012).

Table 2 Technologies for Measuring Queue Length

Technology	Measurements	Advantages	Disadvantages
Inductive Loop Detectors	- Detect occupancy times, percent occupancy, and time between detections - Vehicle arrival and departure counts and rates - Two detectors can estimate queue length	- Low installation and maintenance cost - No on-board equipment required	- Requires at least upstream and downstream detectors to monitor queue length - Reliability diminishes with pavement deterioration - Lane closure required to install and maintain - Must be calibrated
Radar Detectors	- Count vehicles across multiple lanes - Classify vehicles by size - Estimate vehicle speeds	- No lane closure for installation or maintenance - No on-board equipment required	- Requires at least upstream and downstream detectors to sense queue length - Vehicles can be missed due to occlusion - Requires calibration - Higher installation cost compared to loops
Video Cameras	- Process the images to compute flow rates at specific locations or track the length of queue or the movement of vehicles	- Very flexible in terms of detection options - No lane closure required for installation or maintenance - No on-board equipment required	- Vehicles can be missed due to occlusion - Does not work well at night and under some weather conditions - High installation and maintenance costs - Cameras require cleaning

Vehicle (Device) Sensors

These sensing systems detect the presence of devices located in the vehicle or on the people in the vehicle. Bluetooth sensors and toll tags are examples of device sensors. Table 3 describes the technologies that are commonly employed to collect data using this approach. The idea is to identify devices at a point upstream of the back of queue and then re-identify them as they leave the queue. Cheng et al. (2012) provide an example of how this can be done using Bluetooth. Takaba et al. (1991) describes another that uses license plate readers or other technologies. The time between these two detections is the time in the system, which for ferry queues is effectively the same as the waiting time. Technically, the delay can be computed by subtracting from these values the minimum time required to travel between the two monitoring points (when there is no queue). These data can be used to create real-time messages about current wait times (with a temporal lag approximately equal to the time in queue) and they can be analyzed off-line (after the fact) to monitor performance. Because of the lag, the next-arriving driver may experience a wait time different from the delay value most recently observed, but background simulation analyses or conversion equations can use the temporal trends in the most recent wait times and create a credible estimate of the delay that the next arriving driver will experience. For some scenarios, if a finer level of detail is desired, sensors can be installed at intermediate locations within the queue and the time to progress from one location to another can be calculated.

Table 3 Technologies for Fixed Point Vehicle Re-identification

Technologies	Measurements	Advantage	Disadvantage
Bluetooth or Toll Tag Readers	- Devices collect timestamps for devices passing the monitoring locations - Elapsed time between readers can be computed for each device (tag)	- Actual time in system can be measured - Flexibility exists in placing the readers, even solar power can be used	- The wait times have a temporal lag - The percentage of "instrumented vehicles" needs to be significant for the measurements to be meaningful - The device must be in discoverable mode to be sensed*
License Plate Readers**	- Cameras are used to take pictures of the license plates - Character recognition software is used to extract the license plate numbers from the camera images - Time stamps are associated with the pictures so that times in system can be computed	- Actual times in system can be measured - No on-board equipment are required - Flexibility exists in placing the cameras at any location	- Out-dated data - Reduce accuracy due to dirt and damage on plates - Potential for vandalism - unclear picture of plate if trucks queued nose-to-tail

*Bluetooth, today, is often disabled or not "discoverable" on smartphones in response to user concerns about security, battery life, and privacy.
** As an example, the NC State Transportation Department has transitioned to the use of license plate readers to grant access to controlled areas of the campus and parking facilities.

Vehicle (Device) Trackers

These systems take advantage of coordinate systems (e.g., GPS) and an always on device (e.g., a cell phone) to monitor the location of a device in real time. Common examples are shown in Table 4. The most common example here is a system that is tracking cell phones using an app, like mapping applications. Minea and Dumitescu (2019) describe a public transit-focused system; Shu et al. (2016) described another WiFi-based system which might work well in localized areas like ferry terminals. Assuming the app is active, the system tracks the location of the devices in real-time and from those trajectories it computes the time to travel from one location (e.g., back of queue) to another (e.g., on board the ferry).

Table 4 Technologies for Vehicle Trajectory Tracking

Technologies	Measurements	Advantage	Disadvantage
Cell Phone Tracking (directly, by service providers)	- Individual cell phones are tracked directly, without the use of an app - Triangulation based on nearby towers is used to locate the phone - The cell phone's location data are used to calculate waiting time in queue	- Wait times can be measured for individual phones - Provides average speeds for the entire queue length - Move-up times can be computed by segment - No special app is required on the phone	- Multiple readings can be taken for a single vehicle if multiple cell phones are on-board - Triangulation has limited accuracy - Requires permission from cell phone service providers to use the data - Cell phones must be turned on - Roaming charges can arise
Cell Phone App Tracking (GPS)	- An app on a phone senses location using GPS and conveys that information to a server as requested - Monuments (fixed locations) are often established to minimize the data retrieved - Differences in time stamps for the monuments are used to compute time between points	- Wait times can be measured for phones that have the app in use - Move-up times can be computed by segment - The app must be installed on the phone and be in use	- GPS location data have limited accuracy - Agreement is required with the app provider to access the data - Sampling rate is limited to those using the app - Privacy concerns may arise - Hampered by tall buildings, tunnels, or dense foliage

Analyses

Studies that focus on data analysis for ferry wait times are sparse. Andersen and Tørset (2019) used descriptive statistics and linear regression to analyze data for several ferry services in Norway and concluded that linear, quadratic, and logarithmic models could be employed for headways up to 60 minutes. The linear model suggests that the average wait time increases by 0.25 minutes for every additional minute of headway. Moreover, the users tend to adjust their arrivals to match the scheduled departure times as headways increase. Rashidi et al. (2018) present an analysis focused on developing metrics for trip travel times, including those by ferry. Zhang et al. (2016) describe a method for predicting short-term trends in traffic volumes at ferry terminals that capitalizes on data fusion techniques. Zhao et al. (2019) similarly present several methods for estimating queue lengths and traffic volumes using probe vehicle trajectories. Although these ideas are posited in the context of traffic signals, they are equally applicable to ferry terminals.

Instrumentation and Analysis

More common are studies that focus on both instrumentation and analysis. The impetus is that the analysis technique is loosely connected to the technology by which the data are collected. Findley et al. (2018) provide compelling evidence that a ferry terminal can be instrumented in such a way that vehicle movements can be monitored and that delays can be estimated. Musci et al. (2011) describe an interesting idea that capitalizes on loop detectors and fuzzy logic. Zhang et al. (2017) used waiting time registrations to predict traffic delays based on Bayesian multiple model combination method using probe data. Zhao et al. (2019) proposed a probe vehicle-based queue estimation method based on probability theory considering low market penetration of the probe vehicles. By exploiting the stopping positions of the probe vehicles in the queue, they approximated the penetration rate of the probe vehicles, and consequently determine the total queue length. Zhu et al. (2015) measured real time traffic queue length by employing the combination of photogrammetry and image processing methods. Shu et al. (2016) used WiFi positioning data in an indoor scenario to estimate and predict queue time. They built and trained a nonstandard autoregressive model using the previous day's WiFi estimation results and actual wait times to predict wait times. Wait time studies on signalized intersection and ferry services have similar features. Cheng et al. (2012) estimated the queue length based on shockwave identification from probe vehicle trajectories. Despite the simplicity of queue length estimation by trajectory of probe vehicles, it may not be feasible for real world application; either a high market penetration of the probe vehicles to identify the shockwave, or prior information about the queue length is necessary.

Results Dissemination

Ferry operators tend to simply present the most recent information as-is, without more detailed analyses, and allow the users to estimate what the wait time will be. Dzieken and Kottenhoff (2007) provide compelling evidence that real-time information about system status (vehicle location) can have positive effects on attitudes toward system use. Operators like Washington State DOT (2020) and New York City DOT (2020) display their schedules on a website. Some, like the Alaska Marine Highway System (2019), provide a website indicating the current location of the ferries. Washington State DOT (2020) has a website that displays the real-time location of the ferries and the status of the waiting areas at each ferry terminal. It maintains a blog that provides near-real-time information about the ferry system's operation and it has apps for smartphone devices. Barone (2019) describes a large-scale monitor screen that has been installed at the St. George Ferry Terminal on Staten Island to display the real-time location of the Staten Island ferries in New York City. The British Columbia Ferry Services (2019) and Cape May-Lewes Ferry (2019) are similar with webcams at all terminals. Houston TranStar (2020) provides both terminal video displays and vessel location information. Although intended for general purpose use, BATS (2019) describes how WiFi service was installed on the Staten Island ferries so that patrons could continue to enjoy broadband access while on-board. There is also evidence that local newspapers sometimes publish information about anticipated delays (Bainbridge Island Review, 2019).

System-Level Analyses

These analyses tend to ask whether technological investments can improve the quality of the service, both from the user's and the operator's perspectives. Ceder and Varghese (2011) sought to see if routes and schedules might be altered to provide more attractive service for the ferries in Auckland, NZ. Washington State DOT (2019) conducted a similar study of alternative service plans. Cullen et al. (2018) did a similar analysis for three Washington State ferries. Lerner and Sawyer (2015) conducted a comprehensive traveler information demonstration project using the ferry services offered by King County (Puget Sound region) as a case study setting. Reimer (2019) did a similar paper study, for the Fauntleroy Ferry service (again in the Puget Sound region); as did Kelly (2018).

Conclusion

Queuing is a pervasive phenomenon in public transport and ferry services. Long wait times in the queue are associated with imbalanced supply and demand for service, which not only negatively affects customers' experiences but also decreases service utilization and efficiency. Uncertainties in waiting time are another important factor affecting passengers' service satisfaction. Providing wait time information reduces the queuing time through self-planning and relieve anxiety. Technologies used to collect wait time data include inductive loop detectors, ranging radar detectors, video surveillance, cell phone tracking, License Plate Recognition, RFID, and GPS. Email service alerts, social media, websites, variable message signs, fixed signs, and pavement markings are different communication technologies used to convey wait times information to ferry passengers.

The research team deployed two available, affordable, and relevant technologies to test the durability and reliability of the most feasible alternatives mentioned in this literature review.

If the North Carolina ferry services had a dedicated smart phone app or a data sharing arrangement with a third-party (e.g., Google or Waze), the location of devices could be tracked, and delay estimates developed. As with the vehicle tracker technologies, there is a lag in the delay observations; the most recently observed delay may not be the delay that will be experienced by the next arriving driver; but the recent observations can be used to estimate the wait time for the next arriving driver. Ferry operators tend to simply present the most recent information as-is, without more detailed analyses, and allow the users to estimate what the wait time will be. This is laudable, and it is probably enough in many cases, but it maybe be too simple for situations like the North Carolina ferries, where the wait times can be long and priority queues (e.g., residents, trucks) are employed.

METHODOLOGY

Following the review of the literature and technology options, the research team deploys two relevant technologies (i.e., BlueTooth and License Plate Recognition Cameras) to test the durability and reliability of the alternatives in terms of detecting the presence of a vehicle, and therefore the time a vehicle enters and leaves the queue. Based on the results from the initial field testing, the research team makes refinements to the data collection system in preparation for final validation and testing. The final field testing includes the refined system and involves a validation of the data collected by the system, and afterwards field data collection at one ferry terminal to test the applicability of the technology.

Data Collection Devices

Bluetooth

Initially, the research team expected that Bluetooth/Bluetooth Low Energy/Wi-Fi detection technology would be the best method to capture vehicle wait times. This technology can capture MAC addresses from devices where Bluetooth or Wi-Fi are enabled. No other personal information is gathered when using this technology.

The research team had access to Bluetooth detection devices from a vendor that they had used for other traffic data collection projects, so these were tested first. This method was effective in capturing some vehicles, but the sample rate was low (9 percent), and this technology is expensive when purchased from a vendor. The team then decided to build their own devices that could also capture Bluetooth Low Energy (BLE) and Wi-Fi pings from enabled devices. This would be much cheaper and potentially capable of capturing a higher rate of waiting vehicles. While this technology did increase the sample rate (approximately 15 percent), it was still too low and considered ineffective at adequately producing accurate real-time wait times for vehicles. Because of these low sample rates and the cost of the out-of-the-box Bluetooth detection devices, the research team determined that license plate recognition would provide the highest sample rate and could potentially provide real-time or close to real-time results, if this route is explored further.

An initial set of data were collected at the Southport-Fort Fisher route and the team extracted the data from the Bluetooth units and processed the video data. Bluetooth data and video were collected at the Southport-Fort Fisher ferry for five days from November 27, 2019 to December 1, 2019. During this time period, only 140 vehicles were captured with the Bluetooth units for vehicles traveling from Fort Fisher to Southport (approximately 28 vehicles per day). Details of the BlueTooth device performance evaluation are listed in Table 5. Based on this evaluation, the research team recommended exploring other methods for capturing wait time information.

Table 5 Performance of BlueTooth Device

Performance Measures	Fort Fisher Terminal Wait Times and Vehicles by Day				Total
	11/27/2019	**11/28/2019**	**11/29/2019**	**11/30/2019**	
Number of Vehicles Observed by Video	120	73	129	268	590
Number of Vehicles that U-turned (Video)	7	24	24	23	78
Average Wait Time for Vehicles Observed by Video	0:22:07	0:26:34	0:21:17	0:12:39	0:20:39
Number of Vehicles Observed by BlueTooth	48	21	41	59	169
Average Wait Time for all Vehicles Observed by BlueTooth	0:07:07	0:10:15	0:07:17	0:05:38	0:07:34
Average Wait Time for Vehicles Observed by BlueTooth confirmed by video	0:10:37	0:14:12	0:15:00	0:12:39	0:13:07
Number of Vehicles Observed by Both Methods	16	5	11	22	54
% Matched with BlueTooth (and verified by video)	**13%**	**7%**	**9%**	**8%**	**9%**
Average Wait Time for Vehicles Observed by Both Methods	0:17:27	0:21:33	0:16:25	0:22:28	0:19:28
Average Difference Between Wait Time for Vehicles Observed by Both Methods	0:02:27	0:00:46	0:01:29	0:01:41	0:01:17

License Plate Recognition (LPR)

This research used HIKVISION 7 Series License Plate Recognition (LPR) ultra-low light smart cameras, as illustrated in Figure 2. They can automatically capture vehicle images and recognize the vehicle license plate. They use a two-stage process to capture the plate numbers: 1) capture the subject vehicle and locate the license plate, and 2) read the license plate numbers. Using deep learning vehicle detection technology, the LPR camera first determines if a detected object is a vehicle (which can be referred to as a “capture”). When a vehicle is identified, the LPR camera determines where the license plate is based on the features of license plates including the license plate format and the alphanumeric characters that constitute a license plate. Then, the LPR system extracts the characters of the determined license plate candidate via artificial intelligence such as character separation and character recognition, which can be referred to as a “read” (Chang, et al., 2004; Du et al., 2013; HIKVISION, 2021). Moreover, the LPR camera adopted by this research can track the forward or reverse direction of travel, which enables recognizing and differentiating vehicles both approaching and leaving the ferry terminal (HIKVISION, 2021). This is considered critical for identifying and removing invalid samples when estimating vehicle waiting time. Note that one potential limitation of this technology as it relates to these study locations is that the North Carolina DMV only requires license plates on the rear of vehicles, not the front. This limited the potential installation locations of these cameras, as the rear of vehicles had to be visible to capture license plates.

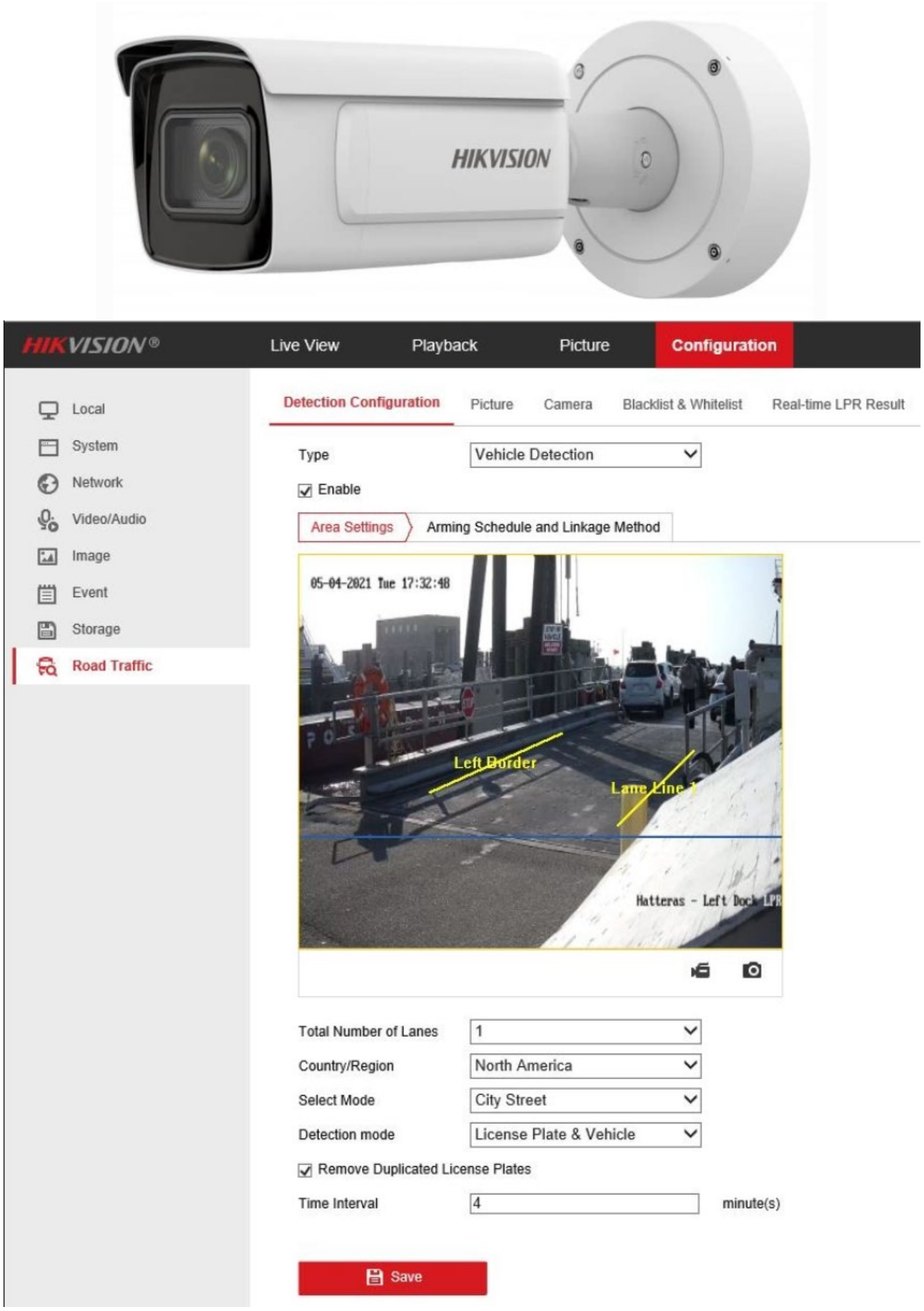


Figure 2 The LPR Camera employed by this research: (a) HIKVISION LPR Camera, (b) LPR Camera Detection Zone

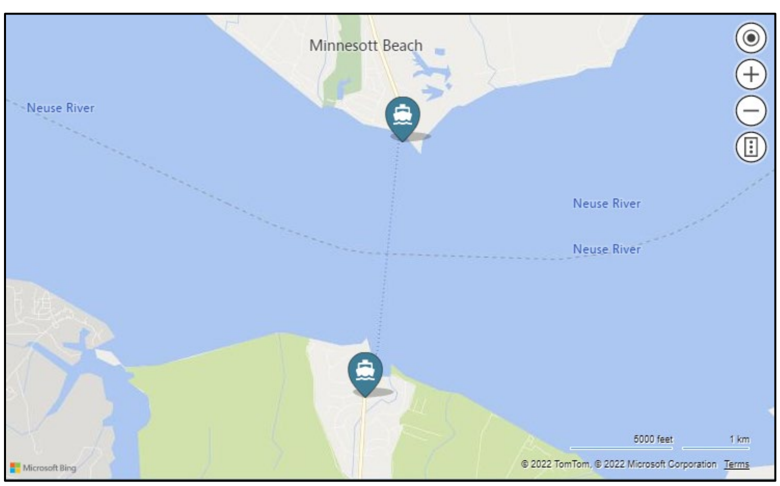
An example of the LPR output results is shown in Figure 3, including the plate reading (i.e., PA2044) and the time the plate was captured (i.e., 16:22:56 on May 4, 2021).

Photo by Daniel Coble; vehicle in the image was a NCSU owned traffic survey vehicle
Figure 3 License plate recognition camera

Data Collection Sites

Cherry Branch

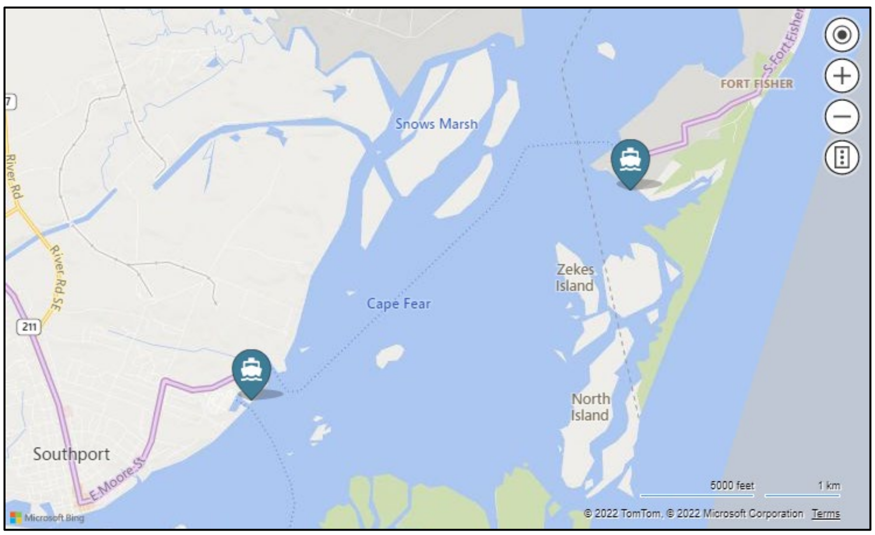
The Cherry Branch Ferry Terminal in North Carolina was the pilot site for this project, including testing of Bluetooth, BLE, Wi-Fi, and LPR technology. The Cherry Branch-Minnesott Beach route (as illustrated in Figure 4) connects Cherry Branch to Minnesott Beach. There are surface connections between these locations, but the ferry route can be significantly shorter (20 minutes and less than three miles versus one hour and over 50 miles). The overall travel time is dependent on the wait time at the terminal. This route is free and runs year-round on the same schedule, as commuters regularly use this route to get between housing and the military base at Cherry Branch. There are 28 trips each day in each direction, running approximately every 30 minutes to one hour. The first and last departure times from Minnesott Beach to Cherry Branch are 05:25 and 23:00, respectively. The first and last departure times for the reverse trip are 05:00 and 22:00, respectively.



(Source of photo: NCDOT, 2022)
Figure 4 Cherry Branch – Minnesott Beach Route

Southport

The Southport Ferry Terminal in North Carolina was selected as one of the test sites for the LPR technology. The Southport-Fort Fisher ferry route (as illustrated in Figure 5) connects Southport to Fort Fisher. There are surface connections between these locations, but the ferry route provides an option that takes half the time (35 minutes and four miles versus over an hour and over 51 miles) and doesn't require a drive through Wilmington. However, this is dependent on the wait time at the ferry terminal. This route runs year-round, but the schedule can vary depending on the season and day of the week. The cost varies depending on if a vehicle is used and the type of vehicle, but the typical vehicle cost is $7. The ferry operates starting at 05:30 on weekdays and 07:00 on weekends, with the last pickup beginning at 18:15 all week, when originating from Southport and ending at Fort Fisher. This schedule is slightly different for the return trip, beginning pickups at 06:15 on weekdays and 07:45 on weekends, with the last pickup being 19:00 throughout the week. There are 14 trips each weekday during the offseason (mid-September to early April) and 16 weekday trips during the peak season (early April to mid-September). There are 14 trips each day on Saturdays and Sundays throughout the year.



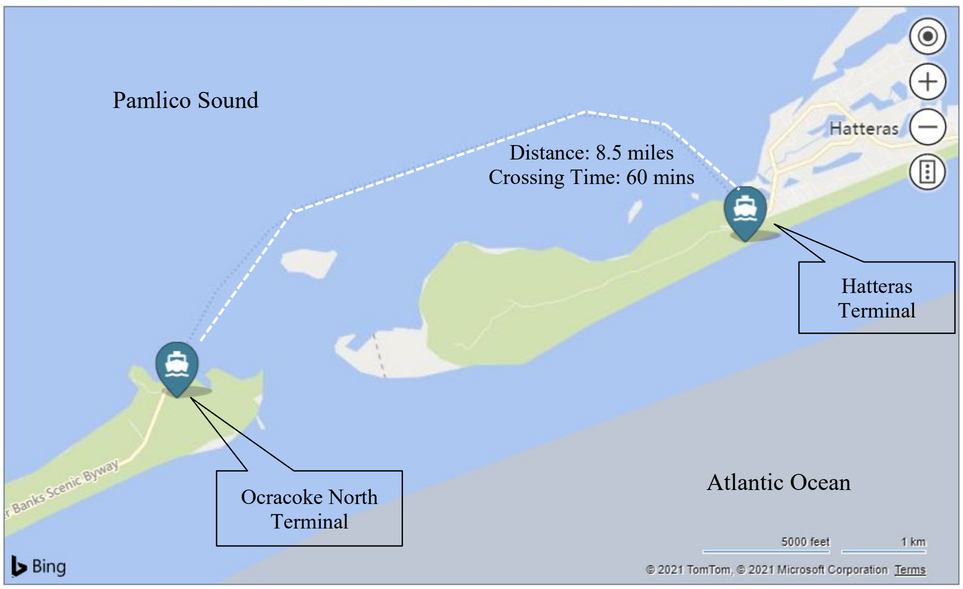
(Source of photo: NCDOT, 2022)

Figure 5 Southport – Fort Fisher Route

Hatteras

The Hatteras Ferry Terminal was selected as another waiting time data collection site. The Hatteras-Ocracoke ferry route (as illustrated in Figure 6) connects Hatteras Island to Ocracoke Island. It transports the highest number of annual ferry passengers in the NCDOT ferry system (NCDOT, 2021). Currently, there are no surface transportation connections between Hatteras and Ocracoke, so the ferry route is the primary way for locals on Ocracoke to leave and return to the island for needed medical appointments or other necessities. Moreover, the Hatteras-Ocracoke route serves tourists; approximately 82 percent of its riders are visitors (Tsai et al., 2010; Bert et al., 2020). Due to the high tourist traffic, the Hatteras ferry terminal has experienced long waiting times for vehicular traffic, particularly during the tourist season (Findley et al., 2018).

There is no toll for the Hatteras-Ocracoke ferry route, and all vehicles are loaded into the vessel based on a first come, first-served rule with the exception of vendors and Ocracoke residents who hold priority passes. The crossing time is 60 minutes and 26 scheduled sailings occur each day (NCDOT, 2021). The ferry operates at a 30-minute sailing headway from 8:00 to 20:00, and there are an additional 6 scheduled sailings in the early morning (i.e., 5:00, 6:00, and 7:00) and later evening (i.e., 21:00, 23:00, and 24:00). The vessels are typically 150 to 180 feet in length and 42 to 44 feet in breadth, with a maximum serving capacity of 30 to 40 passenger vehicles per vessel (NCDOT, 2021). This gives a maximum transporting capability of 80 standard passenger vehicles per hour. The actual serving capacity in terms of the number of vehicles may be lower, depending on the percentage of heavy vehicles such as vehicles with a trailer, recreation vehicles, trucks and buses, etc.



(Source of Photo: NCDOT, 2021)

Figure 6 Hatteras - Ocracoke Ferry Route

Data Collection Procedure

The LPR cameras were temporarily installed at the entrance at the three vessel docks at the Hatteras ferry terminal, as shown in Figures 7 and 8. The distance between the terminal area entrance and the dock is approximately 500 ft. The designed scenarios is for a vehicle to first be captured by the upstream (entrance) LPR camera, then the vehicle will be captured by any of the three downstream (dock) cameras. The time difference between the downstream and the upstream cameras could be treated as an approximation of the waiting time of this matched vehicle. In addition, a camera was installed in the vicinity of the stop line of the waiting area to record the number of vehicles that boarded the vessel (as illustrated in Figure 8). The procedure used at the other ferry terminals is identical to the Hatteras ferry terminal setup.

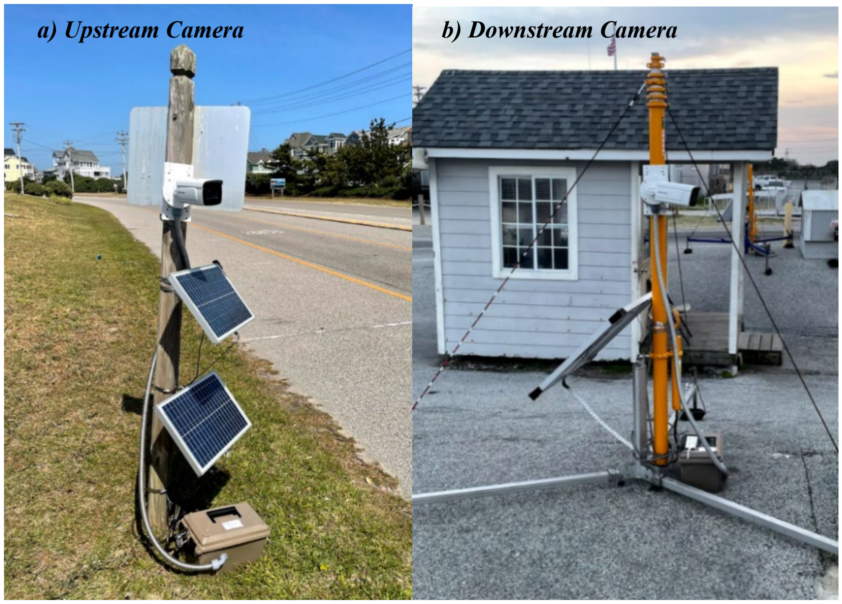


Figure 7 LPR Camera Installation: (a) Upstream LPR camera, (b) Downstream Camera

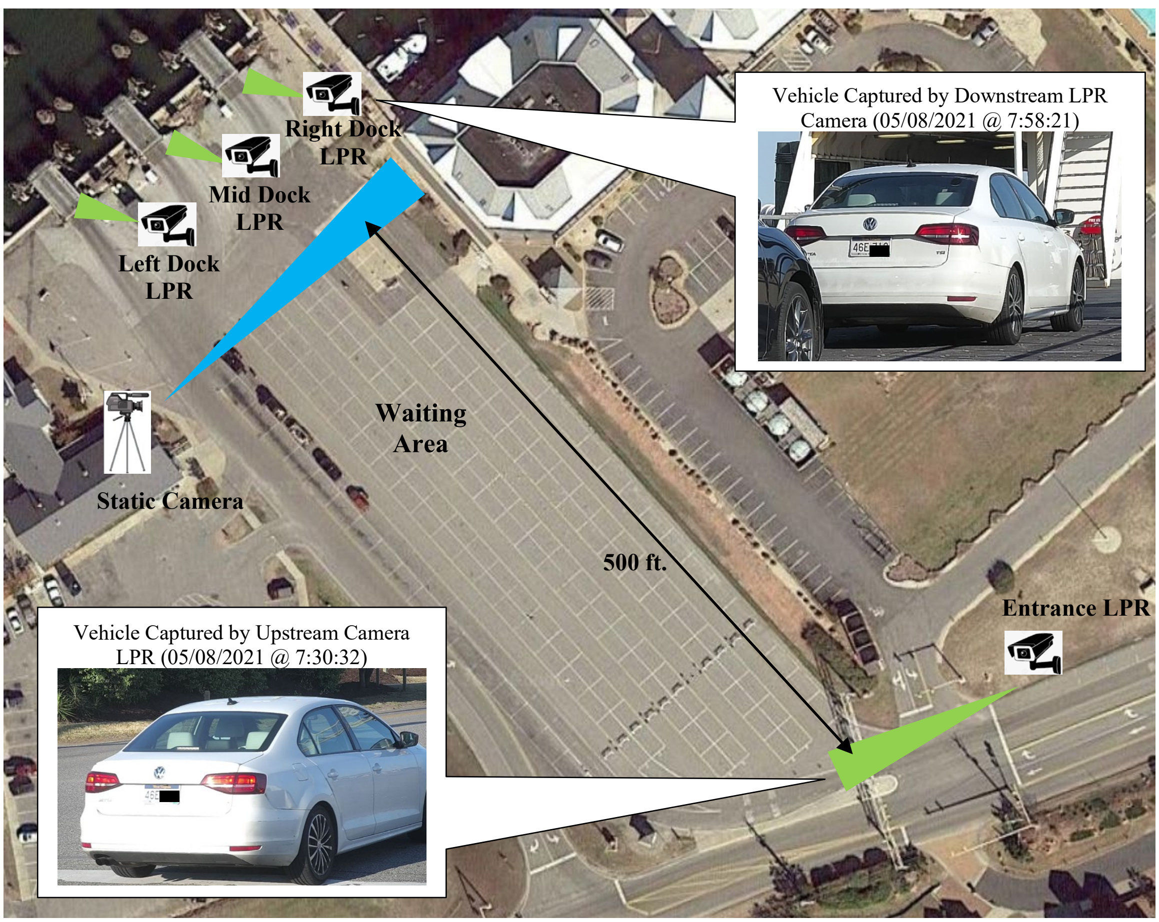


Figure 8 Illustration of LPR camera locations and matched plates at the Hatteras ferry terminal

Performance Assessment

The data processing tasks involved are two-fold: 1) investigate the reliability and accuracy of the LPR system in terms of the vehicle sampling rate, license plate capture rate and read rate, and 2) explore the feasibility of applying LPR cameras for waiting time estimation at ferry terminals in terms of match rate. The definitions of the sampling rate, capture rate, read rate, and match rate are presented below (Findley et al., 2013).

Sampling Rate: the percentage of vehicles photographed by the LPR camera among the vehicles passed by the LPR camera. Note that a photographed vehicle might be a valid or invalid sample (i.e., either with or without a visible license plate).

- Sampling Rate = Number of Vehicles Photographed / Total Number of Vehicles

Capture Rate: the percentage of license plates on vehicles that are correctly identified so they can subsequently be analyzed.

- Capture Rate = Number of License Plates Recognized as License Plates / Total Number of License Plates Studied

Read Rate: the percentage of license plates that are accurately read among the plates that are captured.

- Read Rate = Number of License Plates Accurately Read / Number of License Plates Recognized as License Plates

Match Rate: the percentage of license plates are identified by both the upstream and downstream LPRs. Note that the matched plate might be correctly or incorrectly read. There is not a stipulation that the plate must be legitimate.

- Match Rate = Number of matchable License Plates / Number of Onboard Vehicle License Plates Recognized as License Plates

Waiting Time: the time a vehicle stays in the ferry terminal before it boards a vessel.

- Wait Time = time difference between the timestamps on the downstream and the upstream camera. For instance, in Figure 8 the white sedan was first captured by the upstream camera at 7:30:32; then it was captured by a downstream camera at 7:58:21. The wait time was estimated to be 28 minutes. Note that this assumes the vehicle sat in queue in-between. (It might have left and then rejoined the queue.)

Data Processing

The LPR system produced plate reads including both the recognized plate numbers and un-recognized ones (labeled as "no plate"). An overview of the framework for checking the LPR data processing is illustrated in Figure 9.

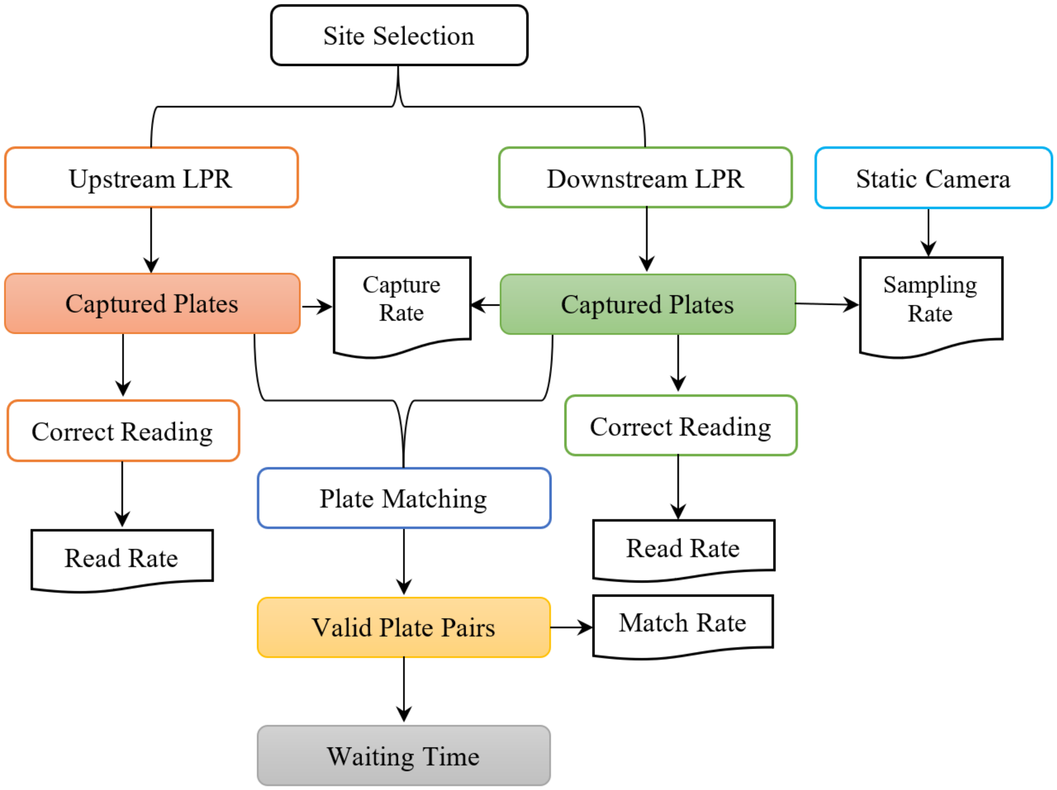


Figure 9 Framework for LPR data processing

The performance analysis procedure can be described as comprising five steps:

- *Step 1*: Manually verify the LPR camera sampling rate by comparing the automatic photographed samples with the actual number of vehicles recorded by the video camera.
- *Step 2*: Manually verify the automatic LPR readings by watching the captured vehicle license plate images. Only valid samples can be used for statistical analysis. Invalid samples include but are not limited to 1) no vehicle in the image; 2) terminal service vehicles that do not have a license plate; 3) LPR camera did not capture a vehicle's license plate due to angle of view; 4) the captured license plate is not visible due to obstructions, dirt, sun glare, etc. Capture rate and read rate were obtained from this step. Moreover, the research also manually corrected the false readings.
- *Step 3*: Group the upstream and downstream LPR readings by day in spreadsheet(s) and match the license plates that were recognized by both upstream and downstream cameras.
- *Step 4*: Manually verify the matched plates, and manually remove the invalid pairs. The match rate is obtained from this step. Typical reasons for the invalid pairs mainly include: 1) duplicate readings, where a plate was captured and read by the same LPR camera more than one time. This usually happens when a vehicle is moving slowly and 2) the downstream camera captures the front plates of vehicles that are disembarking the vessel.
- *Step 5*: Calculate waiting time for each valid pair and conduct descriptive statistical analysis of waiting time distributions.

LPR Camera Performance Assessment

LPR Sampling Rate

The sampling rate refers to the proportion of a population that is sampled. The purpose of investigating the LPR sampling rate is to determine to what extend the vehicles captured by the LPR system can represent the actual on-boarding traffic. This research first identified vehicles (either with or without a visible license plate) that were photographed by the downstream LPR cameras; then, manually extracted the number of vehicles that boarded the vessels from the video camera. Due to technical issues, we were not able to obtain data from the mid-dock LPR camera, so only data from the left and right dock LPR cameras were employed for data analysis, as shown in Table 6. On average, the tested LPR cameras were able to capture 84.2 percent of the boarded vehicles (the research team has no reason to expect that the mid-dock results would differ substantially from the other docks if the camera was operating as expected).

Table 6 LPR Camera Sampling Rates

Date	Left Dock		Sampling Rate	Right Dock		Sampling Rate
	LPR	Static Camera		LPR	Static Camera	
May 5, 2021	241	271	88.9%	30	38	78.9%
May 6, 2021	190	208	91.3%	41	45	91.1%
May 7, 2021	142	167	85.0%	18	25	72.0%
May 8, 2021	199	266	74.8%	16	21	76.2%
Dock Total	**772**	**912**	**84.6%**	**105**	**129**	**81.4%**
Terminal Total	**877**	**1,041**	**84.2%**			

LPR Capture and Read Rates

Table 7 summarizes the capture and read rates for the upstream camera. It had an average capture rate of 83.2% and a read rate of 88.2%. In addition, considering some characters have a similar appearance (e.g., letter "I" and number "1"), this research presented the number of license plates with only one misrecognized character, and employed an "adjusted read rate" to illustrate the potential best read rate the LPR system may perform. For the purposes of estimating wait times, this research presumes that matching license plate readings that have one character difference will increase the sample size without substantially degrading the data quality.

Note that the valid samples listed in Table 7 do not indicate whether the vehicles boarded the ferries. This is because 1) some of the vehicles entered the ferry terminal but did not board; and 2) some front plates were captured for vehicles leaving the terminal. Neither of these conditions ultimately affected the assessment of the performance of the upstream camera, but they introduced some challenges in identifying the vehicles that boarded from the upstream camera.

Therefore, we decided to match the upstream vehicles with those boarded that were identified by the downstream cameras.

The capture rate on May 5 was significantly lower than that for the other days. This is because on that day most vehicles drove on the far side of the unmarked entrance. Because of this, although vehicles were captured by the LPR camera, the image resolution tended to be poor, and the plate could not be recognized by the LPR system.

Table 7 Performance of the Upstream LPR Camera

Date	Valid Sample*	Captured Plates	Capture Rate	Correct Read Plates	Read Rate	1-Miss Read	Adjusted Read Rate
May 5, 2021	875	537	61.4%	466	86.8%	52	96.5%
May 6, 2021	686	595	86.7%	516	86.7%	55	96.0%
May 7, 2021	549	484	88.2%	420	86.8%	43	95.7%
May 8, 2021	581	505	86.9%	443	87.7%	49	97.4%
May 9, 2021	514	484	94.2%	420	88.6%	34	95.7%
May 10, 2021	362	311	85.9%	279	89.1%	27	97.7%
May 11, 2021	502	470	93.6%	429	91.3%	37	99.1%
7 Days Total	**4,069**	**3,386**	**83.2%**	**2,980**	**88.2%**	**297**	**96.8%**

Note: *a valid sample does not necessarily refer to a vehicle that boarded the vessel

For the downstream LPR cameras, again, due to technical issues, only data from the left and right dock LPR cameras were retrieved. We were able to identify 1,267 boarding vehicles over the data collection period. As shown in Table 8, the average capture rate of the LPR cameras was 90.3% and the average read rate was 81.8%. It is interesting to point out that the LPR camera on the right side of the dock had a significantly lower capture rate than the one on the left side. Even so, the read rate for the right-hand LPR was considerably higher than for the left-hand one. A key cause for the differences was that the sample size of the right-hand LPR was significantly lower than for the left-hand one, as the left-hand dock was typically used as the primary dock. Another contributing factor was that the right-hand dock was generally used early in the morning and around noon (when solar glare played a role in the image processing). Additionally, the camera location and lens focal length produced detection errors.

Table 8 Performance of the Downstream LPR Camera

Date	Vessel Dock	Captured Onboard Vehicles with a Visible Plate*	Captured Plates	Capture Rate	Correct Read Plates	Read Rate	1 Misread	Adjusted Read Rate**
May 5, 2021	Left	234	225	96.2%	196	87.1%	20	96.0%
	Right	30	21	70.0%	20	95.2%	1	100%
May 6, 2021	Left	183	181	98.9%	161	89.0%	16	97.8%
	Right	41	23	56.1%	21	91.3%	2	100%
May 7, 2021	Left	135	130	96.3%	117	90.0%	8	96.2%
	Right	18	13	72.2%	12	62.3%	1	100%
May 8, 2021	Left	194	187	96.4%	133	71.1%	35	89.8%
	Right	16	7	*43.8%*	5	*71.4%*	*2*	*100%*
May 9, 2021	Left	169	164	97.0%	120	73.2%	38	96.3%
	Right	5	2	*40.0%*	1	*50.0%*	*1*	*100%*
May 10, 2021	Left	93	89	95.7%	63	70.8%	24	97.8%
	Right	4	3	*75.0%*	0	*0.0%*	*3*	*100%*
May 11, 2021	Left	35	35	100%	28	80.0%	5	94.3%
	Right	110	64	58.2%	59	92.2%	2	95.3%
7 Days Total	Left	1,043	1,011	96.9%	818	80.9%	146	95.4%
	Right	224	133	59.4%	118	88.7%	12	97.7%
Total Docks in a Week		**1,267**	**1,144**	**90.3%**	**936**	**81.8%**	**158**	**95.6%**

Note: *this research assumed only onboard vehicle as valid samples; there are chances that a downstream LPR camera did not capture an onboard vehicle(s) when the vehicles boarding at a very small time or space headway.
Italic numbers: sample size less than 10.

LPR Match Rate

After manually checking the plates detected and matched, a total of 1,006 valid license plate pairs were identified. This suggests the match rate was about 79.4%, calculated as the 1,006 valid license plate pairs identified divided by the 1,267 vehicles that boarded. It is necessary to clarify that the matched pairs include both plates that were correctly read and those that were read incorrectly by both cameras. This match rate is significantly higher than reviewed ITS-based travel time data collection techniques, such as studies that found the match rate for Bluetooth devices ranged from 5% to 15% in a naturalistic driving environment (Bullock et al., 2010; Park et al., 2016; Erkan and Hastemoglu, 2016; Cotton et al., 2020).

Factors Affect LPR Capture and Read Rates

To investigate factors that may affect LPR system performance, this research further analyzed the license plates captured and read by the LPR cameras. Based on a pilot testing conducted prior to the full data collection, this research identified three practical factors that may affect LPR system performance: camera lens focal length (long focal length vs. short focal length), environment (daytime vs. night), and license plate format (standard vs. variant). Among the four LPR cameras, the upstream camera and the right dock camera employed a long-focal length lens (near focal length 8 mm to far focal length 32 mm), while a short-focal length lens (near focal length 2.8 mm to far focal length 12 mm) was applied to the left dock camera and the mid dock camera. This research defined daytime as the time from sunrise to sunset, and the daytime during the data collection period was determined as from 6:00 to 20:00 U.S. Eastern Standard Time. In terms of license plate format, since each state in the U.S. has its unique standard format(s), this research defined a standard license plate format as having all the characters in the same size and font without graphic pattern(s) that are close to the characters displayed on the license plate. Effects of these factors on LPR camera performance are presented in Table 9.

Table 9 Effects of Various Factors on LPR Camera Performance

Factor	Cohort	Valid Sample	Captured Plates	Capture Rate	Correct Read Plates	Read Rate	1-Miss Read	Adjusted Read Rate
Focal Length	Long	4,293	3,519	82.0%	3,098	88.0%	309	96.8%
	Short	1,043	1,011	96.9%	818	80.9%	146	95.4%
Envir.	Day	3,885	3,225	83.0%	2,857	88.6%	276	97.1%
	Night	184	161	87.5%	123	76.4%	21	89.4%
Plate Format	Standard	3,740	3,132	83.7%	2,831	90.4%	242	98.1%
	Variant	329	254	77.2%	149	58.7%	55	80.3%

For camera focal length, this research revealed that the short-focal length LPR camera has a considerably higher capture rate (14.9 percent higher) than the long-focal length LPR camera, while the read rate of long-focal length LPR camera is 7.1 percent higher than short-focal length LPR camera. This is mainly because a short-focal length camera typically has a wider angle of view thus it can more easily capture a license plate. In comparison, a long-focal length camera usually can provide a zoomed-in view of a license plate, which makes the captured license plate more easily being recognized.

In terms of environmental effects, it was found that LPR cameras tend to have a slightly higher (4.5 percent higher) capture rate at night, which is mainly due to the photo contrast of the license plate at night is higher than that during daytime. Nevertheless, the read rate at night is considerably lower (12.2 percent lower) than during daytime, which is mainly due to the image resolution is low at night.

The comparison of standard and variant license plate formats showed that LPR cameras have a slightly lower (6.5 percent lower) capture rate and a significantly lower (31.7 percent lower) read rate on variant license plates than standard license plates. Based on the manual verification of the automatic LPR readings, this research found that character size, rather than the sequence or combination patten of characters, plays the most critical role in read rate. Specifically, LPR cameras had difficulty recognizing multiple letters vertically or diagonally aligned under a relatively smaller size to the main characters (two typical license plate examples are shown in Figure 10), particularly when the image resolution is low. Besides, character font is a key factor to read rate. However, it is worth to point out that under some situations (e.g., low resolution images, side-view images, specialized fonts, etc.), human inspectors may also not able to differentiate the similar characters (such as letter "I" and number "1", letters "O" and "D", etc.).

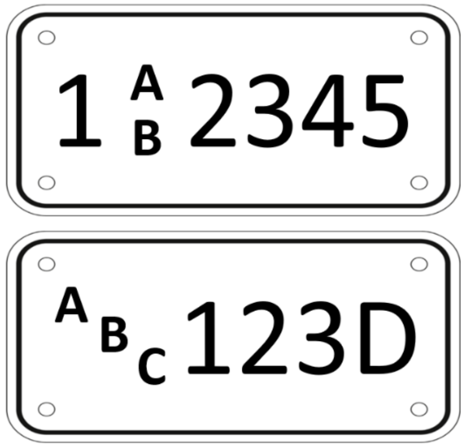


Figure 10 Examples of Vehicle License Plate Formats with a Low Read Rate

Waiting Time Analysis

The major objective of this research was to use the matched LPRs to assess the waiting times experienced by the users. Note that this research was focused more than just the average wait time; we aimed to understand the distribution of waiting time by day and by time.

Percentile Waiting Time by Day

The distribution of the waiting times for each day in a week in May 2021 are shown in Table 10. Values for the 5^{th}, 25^{th}, 75^{th}, 85^{th},and 95^{th} percentiles are shown along with the mean. For example, on Mondays in May, 75% of the wait times was 22 minutes or less, 85% was 25 minutes or less, etc. A graphical depiction of these data is shown in Figure 11.

Table 10 Percentile Waiting Time by Day at the Hatteras Ferry Terminal (May 2021)

Day	Sample Size	Percentile Waiting Time (minutes)						
		5%	25%	Median	75%	85%	95%	Max
Monday	**47**	2	8	16	22	25	28	43
Tuesday	**96**	20	57	75	110	125	130	193
Wednesday	**241**	11	35	62	78	84	104	123
Thursday	**203**	3	21	51	72	86	104	112
Friday	**136**	2	9	18	28	34	45	90
Saturday	**149**	1	12	28	46	51	71	112
Sunday	**134**	3	10	21	31	38	43	87
All Days	**1,006**	3	16	35	65	78	104	193

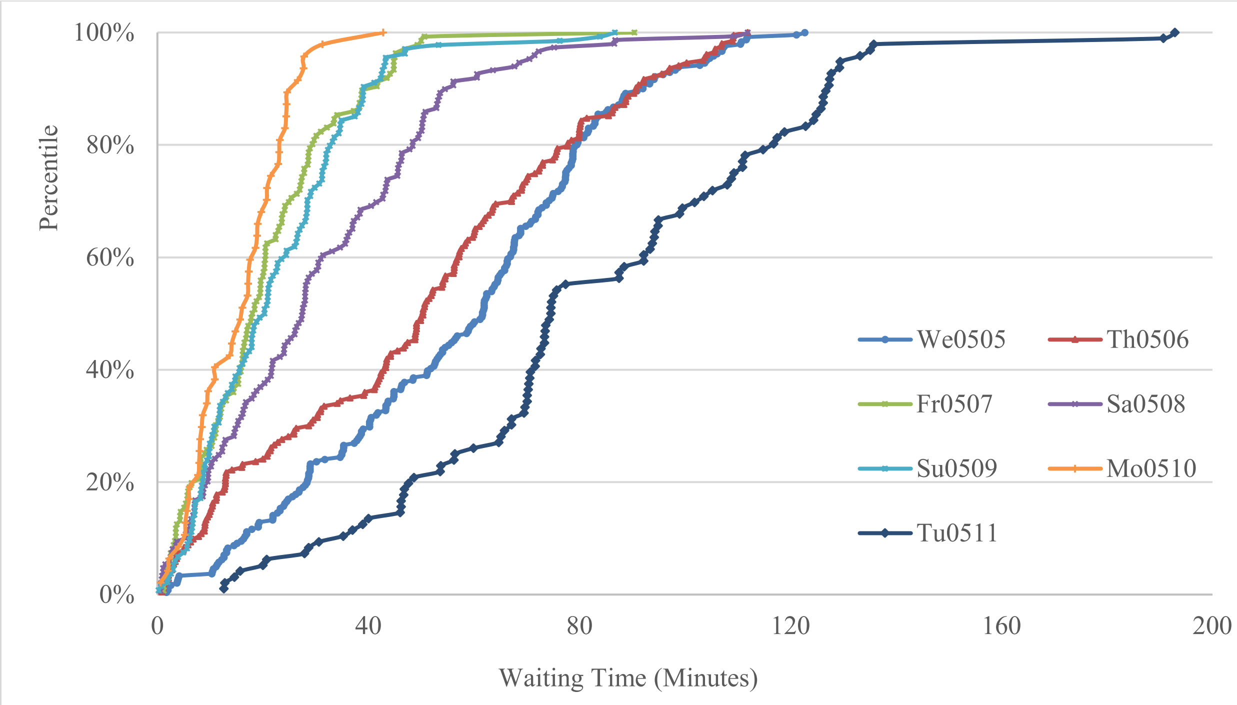


Figure 11 Cumulative distribution function by day at the Hatteras ferry terminal (May 2021)

The distribution of the waiting times for each day in August are shown in Table 11. Similarly, values for the 5th, 25th, 50th, 75th, 85th,and 95th percentiles are shown. It was found that on Mondays in August, 75% of the wait times was 69 minutes or less, 85% was 92 minutes or less, etc. A graphical depiction of these data is shown in Figure 12.

Table 11 Percentile Waiting Time by Day at the Hatteras Ferry Terminal (Aug. 2021)

Day	Sample Size	Percentile Waiting Time (minutes)						
		5%	25%	Median	75%	85%	95%	Max
Monday	**306**	5	21	49	69	92	111	121
Tuesday	**198**	6	24	53	76	81	96	116
Wednesday	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Thursday	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Friday	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Saturday	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Sunday	**248**	2	10	19	28	36	48	80
All Days	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Note: n/a indicates there are missing data for one or more time periods in a day (early morning, mid-morning, noon, etc.), so it is not feasible to estimate percentile waiting times based on these incomplete data.

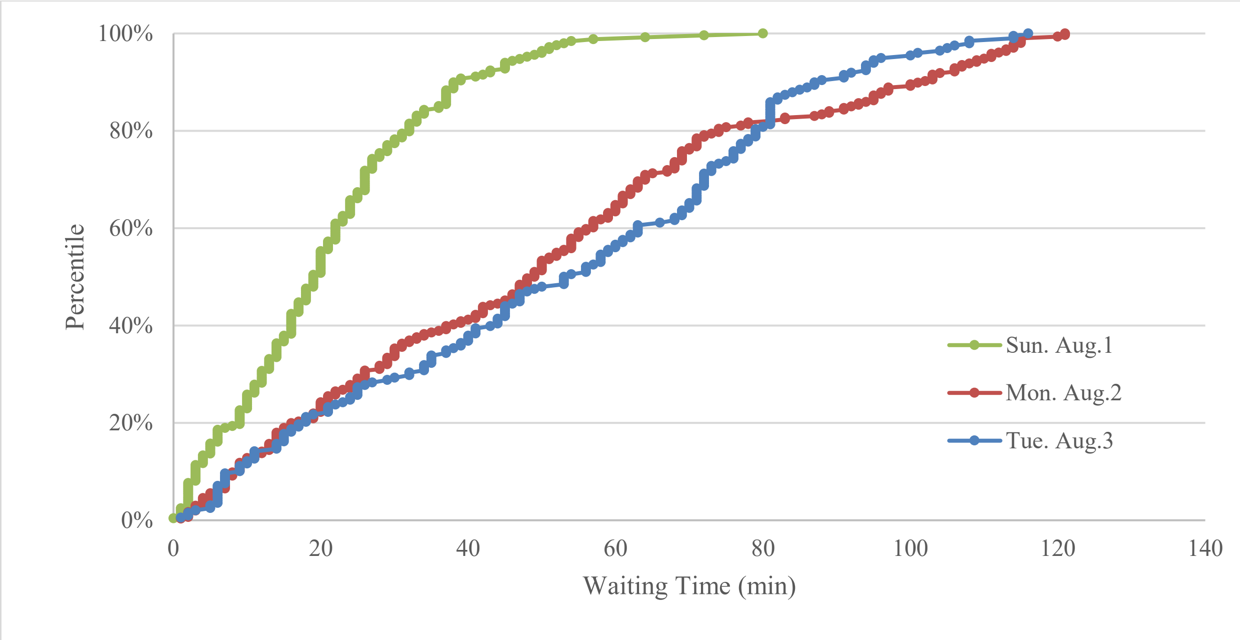


Figure 12 Cumulative distribution function by day at the Hatteras ferry terminal (Aug. 2021)

Given that this is a tourist-focused ferry route, it is not surprising that the wait times on Mondays in May (or other non-peak tourist months) tend to be the lowest values each week. The wait times on weekends (including Friday) are larger because the vacationers, once situated, elect to travel those days to see the Ocracoke Island and other sites. Also, on the midweek days (i.e., Tuesday to Thursday), the waiting times are particularly large, showing the combined effects of the arriving and departing tourism and commute traffic. Note that during the peak tourist month in August, traveling on Mondays will also experience long wait times.

There are several stochastic factors that may affect the waiting time estimation results, such as the performance of the LPR cameras (capture rate, read rate, and match rate), fluctuations in travel demands (particularly when considering the fact that the data collection period was still in the age of COVID-19 pandemic), flexibilities in travel plans, etc. In addition to these stochastic factors, a previous study found that Thursday was a common rental termination day in the Hatteras-Ocracoke tourism industry (Findley et al., 2018), which tends to induce additional trips before or on Thursday, as people begin or end their trips. Another suggestion from local observers is that people who stay from weekend to weekend typically look for another excursion activity mid-week and taking the ferry to Ocracoke Island is a popular option.

Average Waiting Time by Time-of-Day

In addition, the research developed the average waiting time by time-of-day, as shown in Table 12 (May 2021)and Table 13 (August 2021). Generally, in non-peak tourist months (such as in May), travelers who arrived mid-day (10:00 to 14:00) experienced the longest average waiting time. Boarding vehicles typically needed to wait a minimum of one sailing before boarding a vessel. This was particularly significant during Tuesdays, Wednesdays, and Thursdays, where on average a vehicle waited two to three sailings before boarding a vessel.

In the off-peak, such as in the early morning, there were cases where the trends in the average wait time seemed counterintuitive. A manual review of the LPR detections found that this was mainly caused by 1) low sample sizes, such as less than 5 onboard vehicles per sailing; and 2) sailing headways were significantly higher than those that typified the mid-day period. Hence, off-peak vehicles experienced long wait times if they arrived before the first scheduled sailing (such as there were several vehicles arrived at the terminal just past 4:00 am, while the first sailing is scheduled at 5:00 am).

Table 12 Average Waiting Time by Time-of-Day at the Hatteras Ferry Terminal (May 2021)

Day	Average Waiting Time (minutes) by Time-of-Day							
	~ 6	6 – 8	8 – 10	10 – 12	12 - 14	14 - 16	16 - 18	18 ~
Monday	n/a	n/a	n/a	14	*14*	*22*	n/a	n/a
Tuesday	n/a	n/a	n/a	95	78	*20*	16	n/a
Wednesday	*18*	*46*	47	77	69	32	*23*	n/a
Thursday	*27*	n/a	14	61	75	22	20	n/a
Friday	*30*	*12*	26	13	29	6	*12*	*16*
Saturday	n/a	18	21	32	48	26	*10*	n/a
Sunday	*25*	n/a	25	15	32	14	*13*	n/a

Note: n/a: no matched data available; S: sample size; s.d.: standard deviation;
Italic numbers: sample size less than 10;
Red cell: Avg. waiting time > 60 mins, or two sailings; Orange cell: Avg. waiting time > 30 mins, or one sailing; Yellow cell: Avg. waiting time > 15 mins; Green cell: Avg. waiting time < 15 mins

Table 13 Average Waiting Time by Time-of-Day at the Hatteras Ferry Terminal (Aug. 2021)

Day	Average Waiting Time (minutes) by Time-of-Day							
	~ 6	6 – 8	8 – 10	10 – 12	12 - 14	14 - 16	16 - 18	18 ~
Monday	*17*	33	34	82	68	33	19	38
Tuesday	*33*	19	59	66	58	*29*	14	32
Wednesday	n/a	n/a	n/a	138	85	57	34	16
Thursday	n/a	n/a	n/a	89	122	*96*	15	*22*
Friday	n/a	n/a	n/a	111	74	53	8	*25*
Saturday	n/a	n/a	n/a	n/a	67	52	30	44
Sunday	*28*	22	20	16	25	20	11	34

Note: n/a: no matched data available; S: sample size; s.d.: standard deviation;
Italic numbers: sample size less than 10;
Red cell: Avg. waiting time > 60 mins, or two sailings; Orange cell: Avg. waiting time > 30 mins, or one sailing; Yellow cell: Avg. waiting time > 15 mins; Green cell: Avg. waiting time < 15 mins

In peak tourist months (such as in August), waiting times have a generally similar trend as in May but the average waiting times are much longer. Again, travelers who arrived mid-day (10:00 to 14:00) experienced the longest average waiting time; during weekdays, boarding vehicles typically needed to wait a minimum of two to three sailings before boarding a vessel. This was particularly significant during Wednesdays and Thursdays, where a vehicle may have to wait up to four sailings before boarding a vessel.

Presenting these distributions to the customers, we think would help them better plan their trips by encouraging them to, based on their time flexibility, either arrive earlier, or wait until after the peak departure time. Also, this information can provide them with a general idea of the waiting time during the peak periods.

RESEARCH PRODUCTS AND RECOMMENDATIONS

The NCDOT ferry system serves diverse populations on and visitors to the eastern seaboard of the state, ranging from routes that serve daily commuters to those that serve tourists. As a unique transit mode, the operational feature of a vehicle ferry route is significantly different from other transportation modes. Being limited in capacity and constrained by sailing headways, queuing and waiting are inevitable. However, measuring and communicating waiting times are not simple and not currently available to travelers at the study location. In practice, providing waiting time information to ferry users will improve their riding experience.

This research provides information that can be used by the Ferry Division and other NCDOT staff to understand the advantages and disadvantages of various technologies for measuring wait times. Based on a series of pilot tests, the research team recommends applying License Plate Recognition (LPR) technology for tracking and estimating waiting times at ferry terminals. Major findings from this research are presented below.

LPR Camera Performance

In terms of the performance of LPR cameras, this research revealed that in a naturalistic driving environment, the tested LPR cameras were able to photograph approximately 85 percent of the entire population of vehicles that on-boarded the vessels. Among the photographed samples, the average LPR camera capture rate and read rate were 84.3 percent and 87 percent, respectively. The match rate was found to be approximately 80 percent. LPR camera performance assessment results proved that LPR technology is a reliable and robust approach to track and estimate waiting time at ferry terminals with a significant higher match rate than the prevailing ITS-based data collect technologies such as Bluetooth devices.

Through manual review and verification of the LPR images, this research summarizes several key factors that affect LPR camera performance. Findings from this research are mostly consist with previous research efforts (Chang et al., 2004; Du et al., 2013), including but not limit to the following aspects:

LPR Camera Setting

The LPR cameras have very specific installation instructions. As such, the cameras could only be installed where the following conditions were met. This was not always possible with the existing infrastructure, meaning the infrastructure had to be manipulated in order to meet these requirements. This research found that the vertical angle had to be less than 15° and the horizontal angle less than 30° from the location of the observed vehicles. The camera had to be installed between three and five feet off of the ground when observing a level surface. The camera settings likewise had to be adjusted depending on speed of the vehicles. Specifically, the shutter speed and exposure rate of the camera had to be adjusted for slower or faster moving vehicles to ensure the camera could capture a clear image of the license plate and read it properly.

In terms of camera setting, this research found that capture rate of the short-focal length LPR camera was 14.9 percent higher than the long-focal length LPR cameras, while its read rate was 7.1 percent lower than the long-focal length LPR cameras. This is because a short-focal length camera provides a wider angle-of-view and thus increases the probability of capturing a license plate. In comparison, a long-focal length camera usually provides a zoomed-in view of a captured license plate, which facilitates the recognition of a captured license plate.

Environmental Factors

This research compared the performance of LPR cameras at daytime and at night environments. Results show that the capture rate was 4.5 percent higher at night than during the daytime. This is mainly because a license plate has a better reflectivity than the vehicle body, thus the license plate has a higher contrast at night, which made it easier to capture. However, due to the relative low image resolution, the read rate at night was 12.2 percent lower than at daytime.

Besides, it is worth to point out that during daytime, other environmental factors such as sun glare, shadows, adverse weather events, obstructions, background images on the vehicle (e.g., phone numbers or other letters/numbers stamped on the vehicle), etc. also play an important role in LPR camera capture rate as they tend to deteriorate the quality of license plate images.

Plate Format

License plate format appeared to be a key factor that affects the performance LPR cameras, particularly the read rate. For example, the standard license plate in North Carolina has three letters to the left and four numbers to the right, while customized license plates may have any number of characters with more variability in the size of letters and numbers. Moreover, this research found that character size plays the most critical role in read rate, particularly if multiple letters vertically or diagonally aligned under a relatively smaller size to the main characters (in the case of specialty license plates). Variations in letter and number fonts also affect LPR camera read rates, such as the research found many cases where the LPR system could not differentiate the similar characters such as the letter "O" and the letter "D" or the letter "I" and the number "1".

Traffic Flow Condition

In addition to the previous three commonly recognized aspects, this research, through a comparison between the capture rates of the upstream and downstream LPR cameras, found that traffic flow conditions also affect LPR camera performance. Onboard traffic usually arrives at the terminal at a relatively random pattern, so the upstream camera tends to capture the plates more easily. In comparison, at the downstream of the terminal, the queued vehicles board the vessel in a platoon with small headways, which presents challenges to the downstream LPR cameras to capture the license plates. Likewise, as mentioned above, the state of North Carolina does not require license plates on the fronts of vehicles, which limited the installation/observation options of the cameras.

Ferry Terminal Waiting Time

Based on the analyses of the matched license plates in May and August, this research concluded that at the Hatteras ferry terminal, travelers tend to experience long waiting time during the mid-day period between 10:00 and 14:00, particularly during midweek days. Besides, waiting times in peak tourist months (such as in August) are generally higher than in non-peak tourist months (such as in May). Waiting times estimated from the LPR pilot for May 2021 were consistent with the heatmap titled "Plan Your TRIP - Recommended Times to Travel", which was developed based on the waiting times collected at the Hatteras Terminal in 2019 (Figure A1 in Appendix A). Besides, despite there are some missing data, waiting times estimated from the LPR pilot for August 2021 were consistent with the heatmap developed based on the waiting times collected at the Hatteras Terminal in 2021 (Figure A2 in Appendix A).

In terms of factors that affect waiting time, the research summarized that because the capacity of the ferry route is limited (i.e., less than 80 standard passenger vehicles per hour), demand will be the primary factor for waiting time during the mid-day peak period. While during the early morning and later evening non-peak periods when the ferry route operates at a longer sailing headway, travelers' arrival time in terms of proximity to the scheduled ferry departure time appears to be most critical factor to their waiting time.

The percentile waiting times by day and the average waiting times by time-of-day presented in this research have the potential of assisting travelers with planning their trips. Moreover, findings from this research could provide NCDOT operators with insights into developing strategies to improve ferry level-of-service during peak periods, such as ferry scheduling and vessel upgrading.

NCDOT can use the developed research products to inform decisions relating to services and optimizing scheduling. This could improve traffic modeling and overall efficiency. NCDOT can use the developed research products to inform decisions about installing wait time measurement equipment. Additionally, the Ferry Division could use this information to better educate and inform customers about peak times and potential wait times.

Study Limitations and Camera Installation Impacts

The estimated waiting time represent the Hatteras ferry terminal traffic operations under COVID-19 impacts, where the tourism demand might differ from the normal tourist season. Additionally, the LPR match rate represents a population of vehicles that were captured onboarding by the downstream LPR cameras. Since there is the possibility that the downstream cameras did not capture all the onboard vehicles due to technical limitations (e.g., field data showing that when two or more vehicles boarding the vessel at a very small time or space headway, the LPR camera, being limited by the angle of view, can only capture one vehicle). On average, the sampling rate of the downstream LPR cameras was 84.2 percent, indicating that the LPR cameras were able to collect approximately 85 percent of the entire on-boarded vehicles. Unfortunately, we can neither assume the missed vehicles as "matchable plates" nor "non-matchable plates", since there is no evidence showing if the LPR cameras could correctly or incorrectly read these plates.

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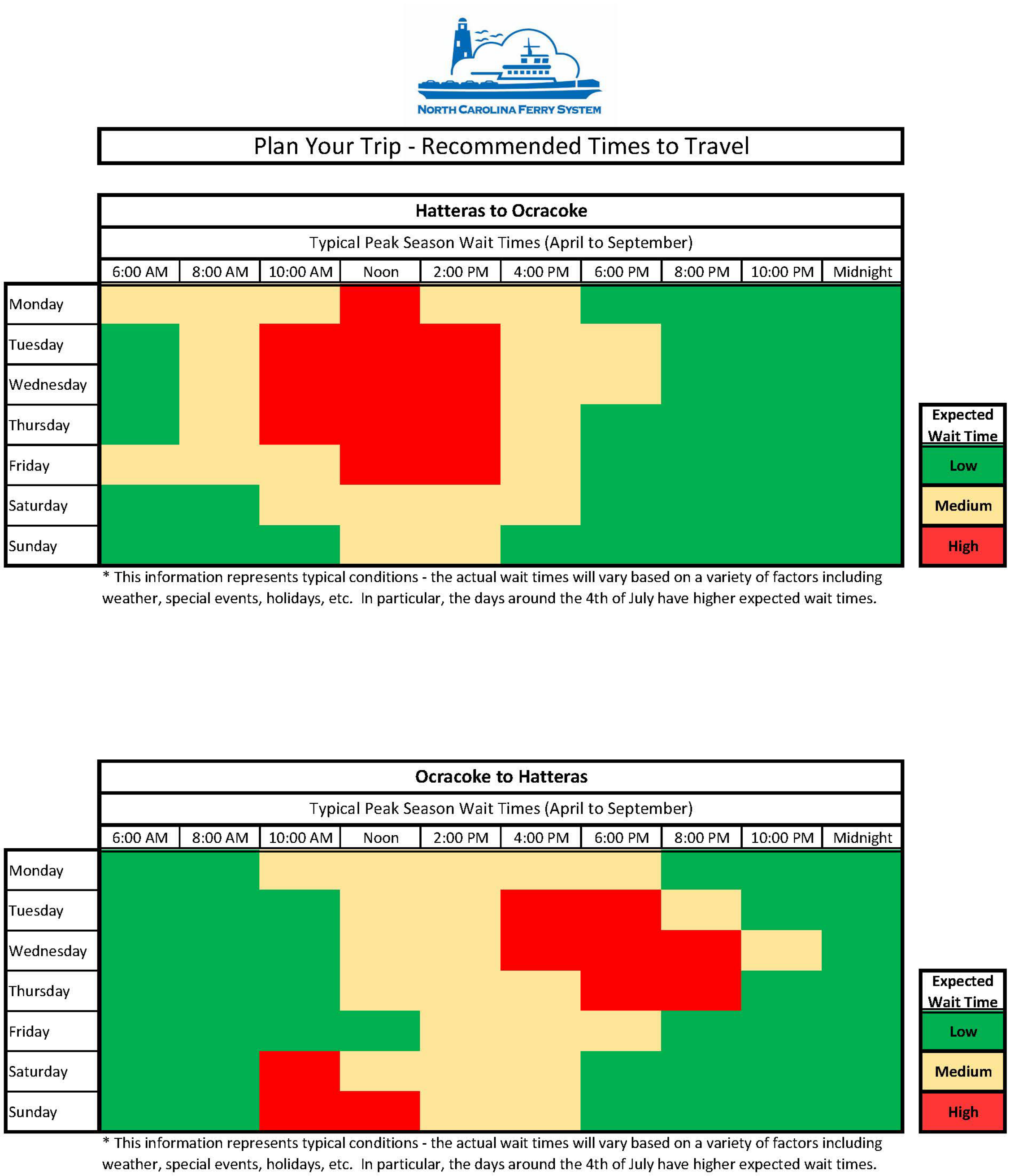
APPENDIX A: WAIT TIME HEAT MAPS FOR HATTERAS/OCRACOKE ROUTE



Based on 2019 Service and Schedule; ITRE Analysis - Congestion levels represent sailings from the 2019 season and may vary for special events or holidays.

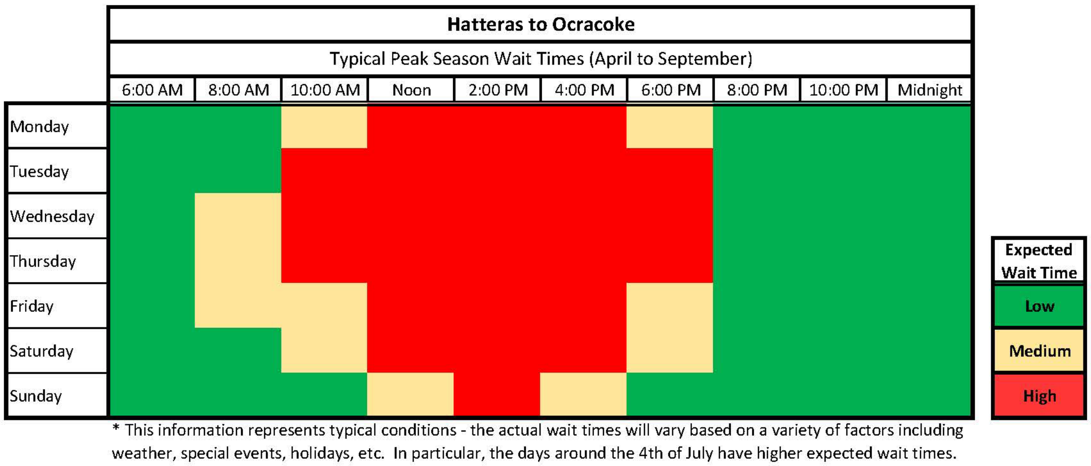
Figure A1: Estimated Waiting Times for the Hatteras-Ocracoke Route (2019)

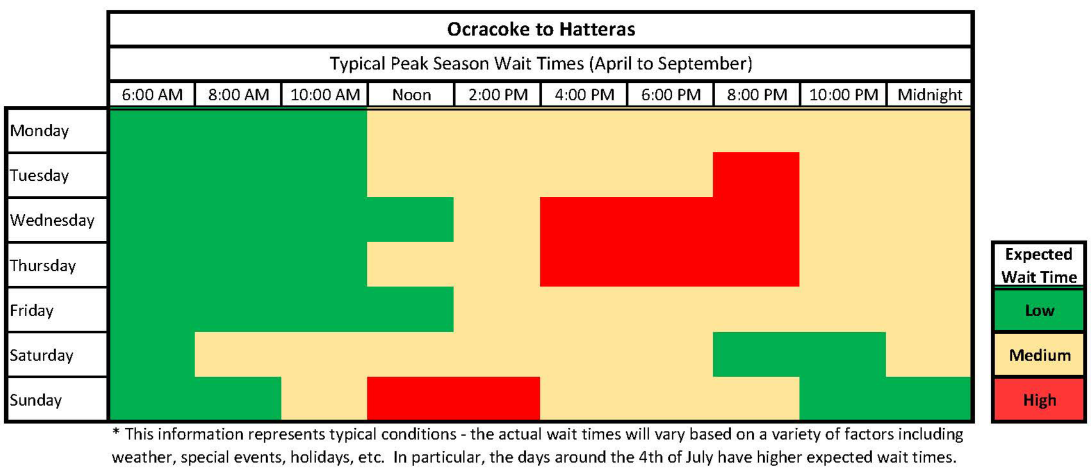
Based on 2021 Service and Schedule; ITRE Analysis - Congestion levels represent sailings from the 2021 season and may vary for special events or holidays.

Figure A2: Estimated Waiting Times for the Hatteras-Ocracoke Route (2021)

Plan Your Trip - Recommended Times to Travel

Consider the Ocracoke Expresss Passenger Ferry during periods with long wait times.





Based on 2019 2021 Service and Schedule; ITRE Analysis - Congestion levels represent sailings from the 2019 2021 season and may vary for special events or holidays.

Figure A3: Estimated Waiting Times for the Hatteras-Ocracoke Route (Combined 2019 and 2021)