Investigation of Ferry Wait Time Technology Implementation

NCDOT Project 2024-30
FHWA/NC/2024-30
August 2024

Institute for Transportation Research and Educations (ITRE)

North Carolina State University

Daniel Coble, P.E.
Guanghaun Yang, Ph.D.
Christopher Vaughan, P.E.
Shoaib Samandar, Ph.D.
Daniel Findley, Ph.D., P.E.

STATE OF NORTH CAROLINA DEPARTMENT OF TRANSPORTATION

RESEARCH & DEVELOPMENT

RESEARCH & DEVELOPMENT

Investigation of Ferry Wait Time Technology Implementation

Institute for Transportation Research and Education (ITRE)
North Carolina State University
Daniel Coble, P.E.
Guangchaun Yang, Ph.D.
Christopher Vaughan, P.E.
Shoaib Samandar, Ph.D.
Daniel J. Findley, Ph.D., P.E.

NCDOT Project 2024-30
FHWA/NC/2024-30
August 2024

Technical Report Documentation Page

1. Report No. **NCDOT/NC/2024-30**	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle **Investigation of Ferry Wait Time Technology Implementation**		5. Report Date August 28, 2024 6. Performing Organization Code
7. Author(s) **Daniel Coble, P.E., Guangchaun Yang, Ph.D., Christopher Vaughan, P.E., Shoaib Samandar, Ph.D., Daniel J. Findley, Ph.D., P.E.**		8. Performing Organization Report No.
9. Performing Organization Name and Address **Institute for Transportation Research and Education North Carolina State University Centennial Campus Box 8601 Raleigh, NC**		10. Work Unit No. (TRAIS) 11. Contract or Grant No.
12. Sponsoring Agency Name and Address **North Carolina Department of Transportation Research and Development 1020 Birch Ridge Dr Raleigh, NC 27610**		13. Type of Report and Period Covered **Final Report** August 1, 2023 - April 15, 2024 14. Sponsoring Agency Code **FHWA/NC/2024-30**
Supplementary Notes:		

16. Abstract

The North Carolina Department of Transportation (NCDOT) Ferry Division operates vessels on seven routes along the eastern coast of North Carolina, catering to a variety of users, from tourists to daily commuters. Just like traffic signals on roadways, queuing and waiting are inherent at ferry terminals, and understanding wait times and queue lengths is crucial for customer satisfaction. Currently, NCDOT ferry customers lack real-time information on wait times and queue lengths. To address this, the NCDOT Ferry Division aims to implement technology that accurately measures and tracks wait times. The goal of this project are to expand on the findings from the previous NCDOT/ITRE study that aimed to 1) evaluate and test various options for measuring wait times and 2) recommend a system for tracking and managing wait times to be installed at ferry terminals.

This research conducted another systematic review of the state-of-the-art of technologies that can be used for measuring wait times. This included field tests of different Bluetooth and License Plate Recognition (LPR) technologies from the previous NCDOT /ITRE study to compare their ability to track vehicles and estimate waiting times at ferry terminals. Based on a series of tests, this research revealed that the tested LPR technology has a capture rate of 80 percent and read rate of 86 percent. This suggests a strong likelihood that the LPR technology to achieve a significantly higher match rate than the estimated match rate of Bluetooth devices (ranging from 35 to 55 percent). There are other factors that impact recommendations for use like the physical durability of the devices in which the Bluetooth devices seem to exceed the LPR technology. The wait times found determined from the Bluetooth device data has proprietary post-processing proprietary methods of improving the accuracy of the wait time estimations, though there were still significant deviance from the estimated ground-truth wait times. Therefore, use of the LPR technology is still recommended for tracking and estimating waiting times at ferry terminals due to the robustness and accuracy of the wait time data.

17. Key Words Ferry, Wait Time, Queue, Travel time	18. Distribution Statement		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 63	22. Price

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

DISCLAIMER

ACKNOWLEDGEMENTS

The research team wishes to thank the many individuals of the North Carolina Department of Transportation who contributed to the project. The research team greatly appreciates the tremendous support and efforts received from Catherine Peele, Planning and Development Manager of the Ferry Division. Special appreciation is also given to Jed Dixon, Deputy Director of Operations of the Ferry Division, for his valuable support of the study.

EXECUTIVE SUMMARY

The North Carolina Department of Transportation (NCDOT) Ferry Division operates vessels on seven routes along the eastern coast of North Carolina, catering to a variety of users, from tourists to daily commuters. Just like traffic signals on roadways, queuing and waiting are inherent at ferry terminals, and understanding wait times and queue lengths is crucial for customer satisfaction. Currently, NCDOT ferry customers lack real-time information on wait times and queue lengths. To address this, the NCDOT Ferry Division aims to implement technology that accurately measures and tracks wait times. The goal of this project are to expand on the findings from the previous NCDOT/ITRE study that aimed to 1) evaluate and test various options for measuring wait times and 2) recommend a system for tracking and managing wait times to be installed at ferry terminals.

This research conducted another systematic review of the state-of-the-art of technologies that can be used for measuring wait times. This included field tests of different Bluetooth and License Plate Recognition (LPR) technologies from the previous NCDOT /ITRE study to compare their ability to track vehicles and estimate waiting times at ferry terminals. Based on a series of tests, this research revealed that the tested LPR technology has a capture rate of 80 percent and read rate of 86 percent. This suggests a strong likelihood that the LPR technology to achieve a significantly higher match rate than the estimated match rate of Bluetooth devices (ranging from 35 to 55 percent). There are other factors that impact recommendations for use like the physical durability of the devices in which the Bluetooth devices seem to exceed the LPR technology. The wait times found determined from the Bluetooth device data has proprietary post-processing methods of improving the accuracy of the wait time estimations, though there were still significant deviance from the estimated ground-truth wait times. Therefore, use of the LPR technology is still recommended for tracking and estimating waiting times at ferry terminals due to the robustness and accuracy of the wait time data.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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.

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 a ferry terminal.

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.

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.

For in depth literature review please refer to the initial full research report from NCDOT Research Project Number 2020-34 (Yang, 2022).

TECHNOLOGY REVIEW

This section describes some of the various data sources that can be utilized to obtain vehicle wait time information at ferry terminals. Accurate and reliable wait time data is crucial for effectively managing ferry operations, providing real-time information to travelers, and identifying areas for improvement. Vehicle wait times at ferry stations can be obtained through multiple methods, each with its own advantages and limitations. The following are some common approaches:

Google Maps

Travel time and wait time data for ferry terminals can potentially be obtained through Google Maps. Google crowdsources data from users' mobile devices to estimate travel times on roads and at key locations like ferry terminals.

How It Works

Google Maps primarily relies on GPS data from a large number of mobile devices running Google Maps or other Google services. As users travel along roads and pass through locations like ferry terminals, their mobile devices transmit Anonymous Location Data back to Google's servers. This data includes GPS coordinates, speed, and other sensor information captured at frequent intervals. By analyzing the speeds and dwell times of these devices across a vast dataset, Google can estimate real-time travel times along routes as well as wait times at specific locations like ferry terminals. Their algorithms take into account typical traffic patterns, live traffic incidents, road closures, and other data points to continuously recalculate and update the estimated travel times displayed in Google Maps. Some of the advantages and drawbacks of Google's travel time data are provided in the following sections.

Benefits

- Low cost (data sourced from Google's existing capabilities)
- Low maintenance requirements
- Real-time data access
- Data can be automatically retrieved via APIs
- Easy to disseminate wait time info to public
- Very little post-processing needed

Potential Drawbacks/Challenges

- Accuracy may vary based on number of data points
- Data access is controlled by Google's policies
- Limited coverage of terminal area and access roads. Google's travel time data is strongest for main roads and highways and coverage may be poor for minor roads, ferry terminal areas, and queue zones. This can lead to inaccurate or missing wait time data in the vicinity of terminals.

License Plate Readers (LPR)

LPR systems use cameras to capture and recognize license plate numbers of vehicles entering and exiting the ferry terminal area. By matching entry and exit times, vehicle wait times can be calculated.

How It Works
Camera sensors equipped with license plate recognition technology are installed at strategic points like entry/exit gates to the ferry terminal area. As vehicles pass these points, high-resolution camera snapshots are taken of their license plates. Specialized software uses optical character recognition (OCR) to automatically detect, read, and record the license plate number, along with a timestamp and geolocation data from each camera sensor. This data is stored in a central system. To calculate a vehicle's wait time, the system looks for matching license plate numbers across the entry and exit cameras. It finds the entry record for that plate, and the subsequent exit record. By calculating the time elapsed between these two records, it can determine how long that vehicle spent inside the terminal area waiting for the ferry. This process is repeated continuously as vehicles arrive and depart, compiling wait time data for analysis across different time periods. The average, median and other statistical measures of wait times can be computed based on the full dataset. Some of the advantages and drawbacks of this method are provided in the following sections.

Benefits
- Highly accurate travel/wait time measurements
- Very high sample size (captures almost all vehicles)

Drawbacks
- High setup and maintenance costs for camera infrastructure
- No real-time data access (post-processing required)
- Significant post-processing effort for license plate matching
- Privacy concerns around license plate capture

Bluetooth Sensors
The Bluetooth sensor approach detects and tracks Bluetooth devices like smartphones as they move through the ferry terminal area to estimate travel times.

How It Works
Bluetooth sensors are installed at strategic locations around the ferry terminal, such as entry/exit points and along queueing areas. These sensors continuously scan for Bluetooth devices within their detection radius. When a Bluetooth-enabled device like a smartphone or vehicle system passes within range of a sensor, the sensor detects and records the unique Media Access Control (MAC) address of that device. The sensor also logs supplementary data like the time, date, location coordinates, and signal strength of the device detection. By deploying multiple sensors in a strategic layout, the system can effectively "watch" Bluetooth devices move through the ferry terminal area over time. When the same device MAC address is detected by the entry and exit sensors, the system calculates the travel time for that device based on the difference between the entry and exit timestamps. To improve accuracy, the system applies filtering techniques to remove potential outliers or anomalous readings caused by factors like device signal fluctuations or erratic movement patterns not indicative of normal vehicle flows.

Benefits
- Relatively inexpensive to implement and maintain
- Provides near real-time data

- Easy to disseminate wait times publicly via data feeds
- Requires no opt-in from travelers (detects all Bluetooth devices)

Challenges

- Sample size can be limited by Bluetooth penetration rates
- Regular maintenance of sensors and supporting IT infrastructure required
- Battery life of sensors could be a major issue and making extended data collection challenging
- Robust filtering algorithms needed to remove outliers/abnormal readings
- Privacy concerns around tracking (though data is anonymous)

Summary

Each of the three methods - Google Maps data, license plate reader systems, and Bluetooth sensor networks - offers distinct advantages and faces specific challenges when it comes to monitoring and measuring vehicle wait times at ferry terminals. Google Maps leverages its vast crowdsourced data to potentially provide low-cost, real-time travel time estimates, but may lack sufficient coverage and detail in terminal areas. License plate readers can accurately capture wait times for all vehicles, but require significant infrastructure investment and data processing effort. Bluetooth sensors present a relatively cost-effective middle ground, directly measuring travel times of a sample of vehicles, though battling penetration rates and potential signal issues. If the coverage issues around ferry terminals can be resolved, Google Maps data would likely be the optimal solution given its low costs and easy accessibility. Failing that, Bluetooth sensors are a strong runner-up option that balances costs and accuracy reasonably well. Careful consideration of the strengths, limitations, and costs of each data source will be critical for transportation agencies in implementing an effective ferry wait time monitoring program.

METHODOLOGY

Following the review of the literature and technology options, the research team deployed 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.

The Hatteras Ferry Terminal was selected as the wait time data collection site. The Hatteras-Ocracoke ferry route (as illustrated in Figure 1) 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.

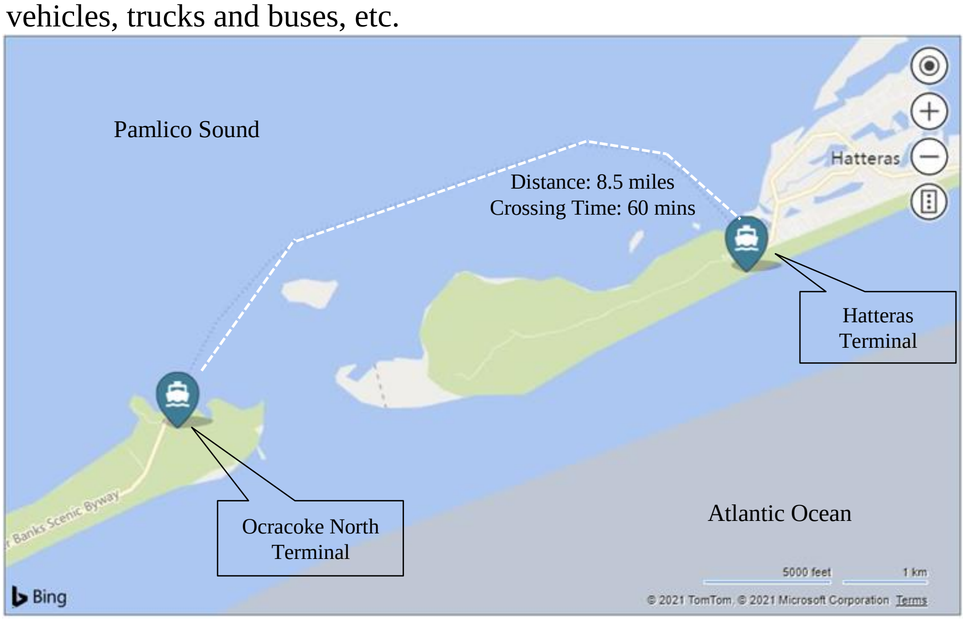


Figure 1: Hatteras - Ocracoke Ferry Route (Source: NCDOT, 2021)

Data Collection Procedures

The data collection devices were installed and calibrated on-location from September 18 to 20, 2023 and then removed from the site on October 2 and 3, 2023. Therefore, the data collection period spans September 21 to October 1, 2023 except for September 22 and 23 as a result of ferry operation interruptions due to Tropical Storm Ophelia.

LPR Install

This research used one Adaptive Recognition Vidar LPR camera (model Vidar 2xFHDx LT U), as illustrated in Figure 2. Full data sheet information on the camera can be found in Appendix A. (Adaptive Recognition, 2024)

The LPR camera was temporarily installed at the entrance at the southwest-most dock (left-most when facing the docks from the vehicle queueing area) at the Hatteras ferry terminal, as shown in Figures 2 and 3. The post used to mount the camera is the same location as the LPR used for the left dock in the previous phase of the project. The left dock was chosen as it is typically the most utilized of the docks as a measure to optimize the sample size of the study. The LPR camera installation included networking hardware to a wireless modem powered by nine 22-amp batteries maintained by a 100-watt solar panel. In addition to the LPR, video cameras were installed around the queueing area to record the number of vehicles that boarded the vessel (as illustrated in Figure 3).

Figure 2: LPR Camera Installation on Left Dock

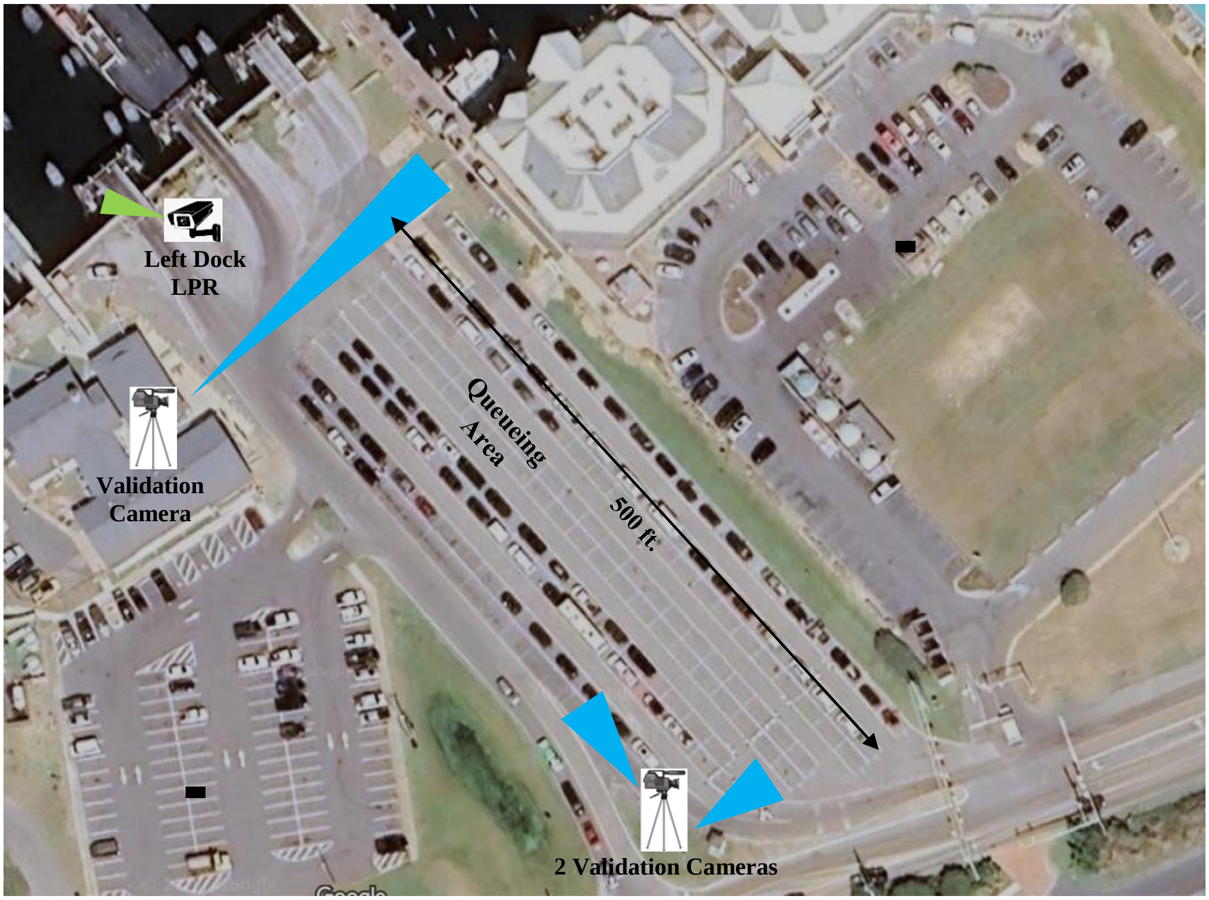


Figure 3: Illustration of LPR and validation camera locations at the Hatteras ferry terminal

SMATS Wi-Fi & Bluetooth Install

This research used two SMATS TRAFFICBOX™ pole-mounted, battery operated Bluetooth and Wi-Fi sensors that are designed for portability. These devices capture Bluetooth, Wi-Fi, and Bluetooth Low Energy (BLE) enabled devices from a range of approximately 200 feet or more. The range of the sensors extended as a radius in all directions due to the utilization of omnidirectional antennas. The sensors can be outfitted with directional antennas instead in cases that benefit from more localized detection areas. The data from each device is uploaded automatically to the proprietary cloud-based traffic data analytics application, iNode™, to be accessed by the end user. Each installation included the SMATS device and battery-maintaining solar panel, as shown in Figure 4. Full data sheet information on the camera can be found in Appendix B. (SMATS, 2024)

The SMATS sensors were installed during the same period as the LPR camera at the Hatteras ferry terminal. Sensor 1 was installed upstream from the ferry terminal adjacent to NC-12 on the upright pole of an overhead sign structure. Sensor 2 was installed on the middle dock post in the same location as the LPR from the previous phase of the project. The devices were installed approximately 2,000 linear feet of roadway away from each other, as shown in Figure 5.

Figure 4: SMATS Hardware Installation Example (without solar panel)[left], SMATS Ferry Sensor 2 Installation [right]

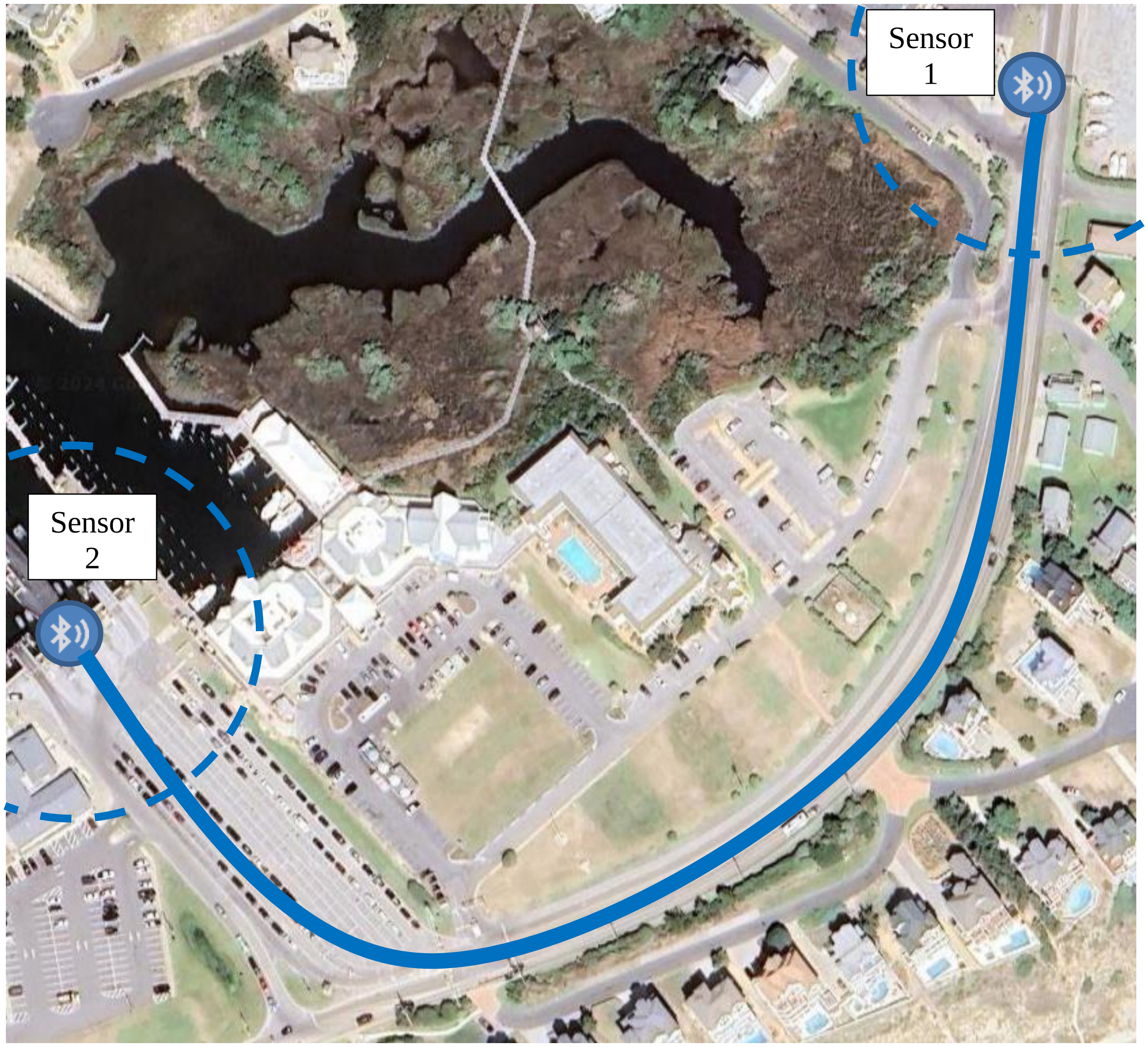


Figure 5: SMATS Devices Install Locations (dashed blue line represents estimated sensor signal range, solid blue line represents travel route for link)

Data Processing

LPR Data Reduction Procedures

The LPR data collected from the camera consisted of a comma separated value (CSV) file containing information about each collected plate's contents as well as information about the vehicle, the confidence of the values for the attributes and when the plate was seen. The LPR camera also collected still images that correspond to each event in the CSV file, as shown in Figure 6. The still images were used to manually validate if the plate contents determined by the LPR in the CSV matched the corresponding still image plate contents.

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 (match rate between multiple LPR cameras could not be collected due only utilizing one LPR camera). The definitions of the capture rate and read rate are below (Findley et al., 2013).

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 Divided by the 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 Divided by the Number of 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 when a vehicle entered the queueing area and when that vehicle departed via one of the three docks. Vehicle wait times were estimated using a first-in-first-out assumption.

Figure 6: LPR Camera View Example

SMATS Bluetooth Data Reduction Procedures

The SMATS TRAFFICBOX™ sensors upload to a proprietary cloud-based traffic data analytics application, iNode™, which can be utilized to filter outlier data from the matched signals along the link created between upstream and downstream sensors (Dion 2006). These sensors and traffic analytics are typically used for travel time analysis, therefore, some of the terms in the settings of the analytics are designed for travel time, and for the purpose of this research, the team was focused on the travel time from beyond the ferry terminal queue to the ferry dock to board, which is comparable to wait time. Since the Hatteras ferry terminal has been known to experience wait times of several hours, the maximum travel time boundaries were set to five hours to allow for excess wait times. The sensors were set to match MAC addresses from the last time they were seen by each device instead of the alternatives of the strongest Received Signal Strength Indicator (RSSI) or first time they were seen. The "last detection" filter parameter was to avoid including time a vehicle potentially spent stopped close to the gas station at Sensor 1, as that wouldn't be time spent in the ferry terminal queue. The "last detection" filter parameter was also to avoid removing time a vehicle potentially spent stopped close to ferry terminal docks at Sensor 2 before actually departing, as that would erroneously reduce the estimate wait time.

To demonstrate the potential influences of some of the filter parameter settings in the raw data of the SMATS iNode^{TM} data, the raw data was analyzed utilizing what this research is referring to as "initial" and "refined" cases of filter parameter settings. The minimum travel time boundary was set to two minutes in the initial case to only take into consideration the estimated drive time from Sensor 1 to Sensor 2, where the refined case used a minimum travel time of five minutes to take into account the estimated drive time from Sensor 1 to Sensor 2 as well as the time that vehicles wait on the ferry once boarded still in range of the sensor. Travel times below this are assumed to be from vehicles that diverted into a parking lot but were close enough to Sensor 2 to be registered though they did not wait to board the ferry. The RSSI filter parameter settings were set at -200 for the initial case to allow for even weak signals to be considered. For the refined case, the RSSI filter parameter setting was set to -90 as that is the threshold for what can be considered "unusable connection", however, this was only changed for Sensor 2 (destination sensor) to reduce the number of vehicles that did not actually board the ferry and get close enough to the sensor for a stronger signal (Li, 2023).

All filter parameters for the initial case are shown in Appendix C and all filter parameters for the refined case are shown in Appendix D.

Validation Video Camera Data Reduction Procedures

To collect comparison data for both the LPR and SMATS devices, three additional video cameras were installed with views covering the entire queueing area recording all day for the duration of the collection period. The videos from these cameras were manually reduced to log vehicles entering (categorized by whether each entered via the priority lane or the standard queue) and exiting (categorized by which dock it departed the queue from [left/mid/right]). Any vehicles that entered the queue but abandoned the queue without departing via a dock was separated from the entering vehicles. Vehicle wait times were estimated using a first-in-first-out assumption within each category. The count of vehicles departing via the left dock was utilized for comparison with the LPR camera. The total count of vehicles from the videos as well as the vehicles' wait times were utilized for comparison to the SMATS device data.

ANALYSIS AND RESULTS

LPR Camera Performance Assessment

LPR Capture and Read Rates

Table 1 summarizes the initial capture and read rates for the Adaptive Recognition Vidar LPR camera. It had an average capture rate of 81 percent and a read rate of 86 percent, however, the capture rate on September 21 exceeded 100 percent. This is expected to be due to the initial assumption that each vehicle has only one plate associated with it when calculating the "valid sample" without consideration for vehicles that may have more than one plate associated with it. This sample is expanded in Table 2 to estimate the total number of plates (i.e. vehicles without trailers or other attachments that might have a plate as well as the vehicle count for one plate, where vehicles with trailers or other attachments that may also have a plate count for two plates).

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.

Table 1: Performance of the LPR Camera (base vehicle count as "Valid Sample")

Date	Valid Sample*	Captured Plates	Capture Rate	Correct Read Plates	Read Rate	Single Digit Incorrect	Adjusted Read Rate
Sept. 21, 2023	146	147	101%*	135	92%	9	98%
Sept. 24, 2023	105	91	87%	76	84%	12	97%
Sept. 25, 2023	158	135	85%	110	81%	20	96%
Sept. 26, 2023	283	255	90%	201	79%	32	91%
Sept. 27, 2023	119	86	72%	75	87%	8	97%
Sept. 28, 2023	221	142	64%	127	89%	13	99%
Sept. 29, 2023	203	140	69%	129	92%	8	98%
Sept. 30, 2023	95	69	73%	63	91%	4	97%
Oct.1, 2023	190	170	89%	148	87%	9	92%
9-Day Total	1520	1235	81%	1064	86%	115	95%

*"Valid Sample" in this table does not take into account that some vehicles may have multiple plates associated with it via trailers

Table 2: Performance of the LPR Camera (estimated plate counts as "Valid Sample")

Date	Estimated Plate Count Valid Sample*	Captured Plates	Capture Rate	Correct Read Plates	Read Rate	Single Digit Incorrect	Adjusted Read Rate
Sept. 21, 2023	147	147	100%	135	92%	9	98%
Sept. 24, 2023	111	91	82%	76	84%	12	97%
Sept. 25, 2023	163	135	83%	110	81%	20	96%
Sept. 26, 2023	289	255	88%	201	79%	32	91%
Sept. 27, 2023	124	86	69%	75	87%	8	97%
Sept. 28, 2023	226	142	63%	127	89%	13	99%
Sept. 29, 2023	213	140	66%	129	92%	8	98%
Sept. 30, 2023	99	69	70%	63	91%	4	97%
Oct.1, 2023	193	170	88%	148	87%	9	92%
9-Day Total	1565	1235	79%	1064	86%	115	95%

* "Valid Sample" in this table does take into account that some vehicles may have multiple plates associated with it via trailers

After taking into account the potential additional plates, the LPR camera is estimated to have captured 100 percent of the plates on September 21, however, the capture rates decline after that date, reaching the lowest of the nine days on September 28 at 63 percent captured before steadily increasing again through the rest of the collection period. Across the entire collection period the average capture rate was 79 percent, the average read rate was 86 percent, and the average adjusted rate was 95 percent. The read rate remained over 80 percent over the entire collection period and the adjusted read rate remained above 90 percent over the entire collection period.

Factors Effecting LPR Read Rates

This research evaluated two major suspected detriments to the LPR read rates: 1) occlusion of the license plates impeding the LPR cameras view of the entire plate and 2) variations of plate formats from standard plate layout (i.e. specialty plates and stacked characters). Examples of these can be found below in Figure 7 and the results of the comparison can be found below in Table 3. The read rate and adjusted read rate dropped 24 percent and 11 percent respectfully from when there was no occlusion to when the plates were occluded. Similarly, the read rate and adjusted read rate dropped 9 percent and 12 percent respectfully from when plates were in a standard format versus when the plate were variant formats.

Table 3: Effects of Various Factors on LPR Camera Performance

Factor	Cohort	Captured Plates	Correct Read Plates	Read Rate	1-Miss Read	Adjusted Read Rate
Occlusion	None	1222	1056	86%	112	96%
	Occluded	13	8	62%	3	85%
Plate Format	Standard	1137	990	87%	107	96%
	Variant	85	66	78%	5	84%

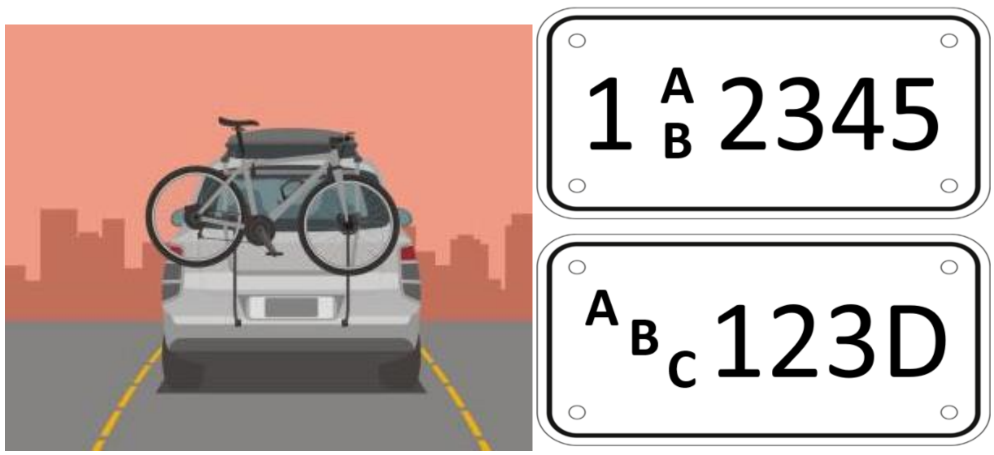


Figure 7: Examples of Vehicle License Plate Formats with a Low Read Rate

SMATS Performance Assessment

SMATS Waiting Time Analysis

The primary objective of this research was to use the data collection technologies 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.

As mentioned in the "SMATS Bluetooth Data Reduction Procedures", the SMATS data was exported with two groups of filter parameters described to as "initial" (with wider boundary limits on filter parameters) and "refined" (with narrower boundary limits on filter parameters). As expected, the narrower refined case resulted in a smaller sample size and therefore reduced estimated sensor penetration rates by filtering out more vehicle trips, as shown in Table 4 below. The penetration rate for the SMATS initial case ranged from 41 percent to 64 percent and averaged 55 percent across the 9-day data collection period. The penetration rate for the SMATS refined case ranged from 25 percent to 42 percent and averaged 34 percent across the 9-day data collection period, a 21 percent reduction from the initial case.

Table 4: Penetration Rates by Day Initial vs. Refined SMATS Cases

Date	Visual	SMATS - Initial		SMATS - Refined	
	# Vehicles	# Vehicles	Est. Pen. Rate	# Vehicles	Est. Pen. Rate
9/21/2023	406	259	64%	163	40%
9/24/2023	352	205	58%	126	36%
9/25/2023	325	164	50%	96	30%
9/26/2023	412	167	41%	104	25%
9/27/2023	315	192	61%	131	42%
9/28/2023	356	210	59%	132	37%
9/29/2023	335	167	50%	100	30%
9/30/2023	296	170	57%	104	35%
10/1/2023	273	161	59%	101	37%
9-Day Totals	*3070*	*1695*	*55%*	*1057*	*34%*

The range of daily penetration rates reduced from the initial case ($\mu_{initial}$-14% to $\mu_{initial}$ +9%) to the refined case (μ_{strict} -9% to μ_{strict} +8%) and the greater range reduction effect was on the lower range boundary that saw a 5 percent reduction in the minimum range boundary difference from the average. This is likely due to a majority of vehicle trips that were filtered from the refined case that otherwise were included in the initial case had lower travel times in the 0-15 minute range (which are important to understand, but likely not as critical as long wait times) from increasing the minimum travel time filter parameter setting in the refined case as seen below in Figure 8.

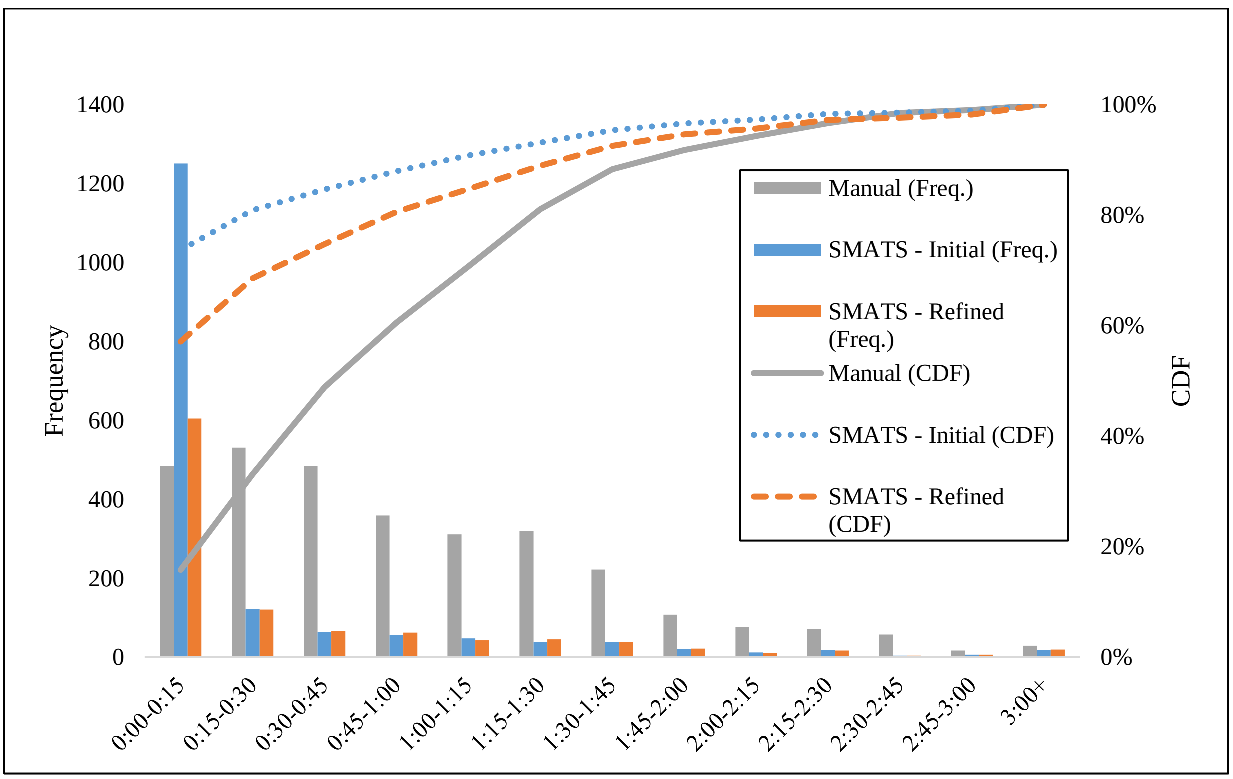


Figure 8: Wait Time Distribution Comparison for Data Collection Period, Visual vs. SMATS Cases

We can also see in Figure 9 that the frequency of wait times in the 0-15 minute range found from the visual (video reduction) data become much closer the frequency of those travel times in the SMATS data for the SMATS refined case versus the SMATS initial case. The cumulative distribution function (CDF) for the SMATS refined case is also closer to the CDF of the visual data then the SMATS initial CDF is to the visual CDF. However, the remaining distributions demonstrate that both the initial and refined cases are significantly skewed toward the lower wait times. As a result, the average travel times of the SMATS initial case are mostly consistently below those of the SMATS refined case and, likewise, the average travel times of the SMATS refined case are consistently below the average wait times of the visual data. An example of this is shown via the comparison of wait times from September 30 in Table 5 & Figure 9 below (for estimated wait time tables & figures of all days see Appendix E).

Table 5: Average Wait Times Comparison for 9/30/2023 Visual vs. SMATS Cases

Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	0:51	0:03	-0:48	0:29	-0:22
06-08	0:21	0:07	-0:14	0:07	-0:14
08-10	0:39	0:10	-0:28	0:19	-0:20
10-12	0:56	0:25	-0:31	0:45	-0:10
12-14	1:13	0:35	-0:38	0:54	-0:19
14-16	1:30	0:41	-0:48	1:11	-0:18
16-18	0:51	0:09	-0:42	0:37	-0:14
18 ~	0:30	0:19	-0:11	0:24	-0:05
Day Avg.	0:58	0:23	-0:35	0:37	-0:20

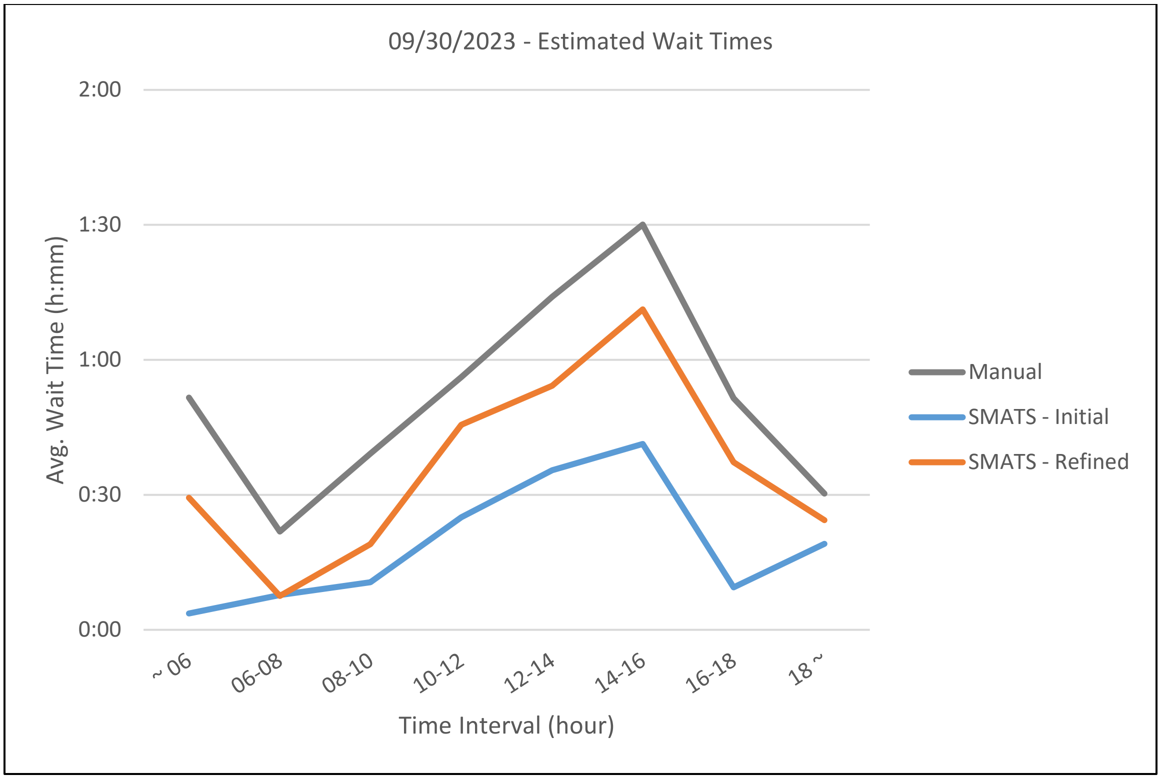


Figure 9: Average Wait Times Comparison for 9/30/2023 Visual vs. SMATS Cases

There were examples of when the SMATS estimates were greater than the visual as seen in Table 6 and Figure 10 below (for estimated wait time tables and figures of all days see Appendix E). The instances where the SMATS seem to overestimate the wait times when compared to the visual estimates time intervals in these examples instead of underestimate seem to happen towards the beginning or end of the day outside of the typical peak times in the middle of the day when the sample size is lower.

Table 6: Average Wait Times Comparison for 10/01/2023 Visual vs. SMATS Cases

Time Interval	Manual	SMATS - Initial		SMATS - Refined	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	0:27	-	-	-	-
06-08	0:26	0:06	-0:19	0:07	-0:18
08-10	0:23	0:21	-0:02	0:32	+0:08
10-12	0:28	0:09	-0:19	0:11	-0:16
12-14	0:29	0:12	-0:17	0:19	-0:10
14-16	0:42	0:15	-0:26	0:21	-0:21
16-18	0:25	0:34	+0:09	0:57	+0:32
18 ~	0:25	0:07	-0:18	0:11	-0:14
Day Avg.	0:30	0:15	-0:14	0:22	-0:08

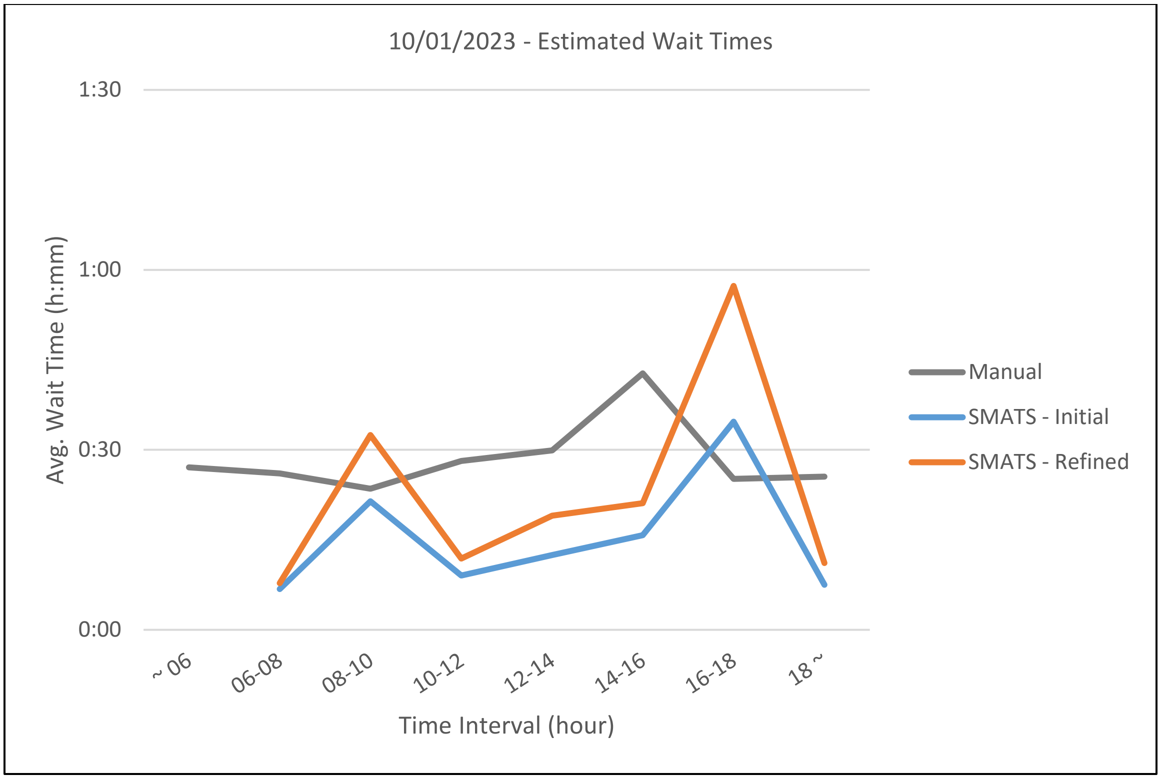


Figure 10: Average Wait Times Comparison for 10/01/2023 Visual vs. SMATS Cases

There is also a trend in the SMATS during some of the days where it seems that SMATS trend lines are shifted one period after the visual data trend lines. This is easiest to spot when tracking the peaks in the data as seen in the example shown below in Table 7 and Figure 11 (for estimated wait time tables and figures of all days see Appendix E). This could come as a result of the visual data time intervals being based on the timestamps that vehicles entered the queue, where the timestamps from the SMATS data were based on the time that an ID was last seen from the destination sensor (Sensor 2) which would be the equivalent to the visual data's exit queue timestamps. However, this was mitigated by subtracting the travel time for each matched ID in the SMATS data from the corresponding timestamp to achieve an estimated time of origin that could better be compared to the visual data's entering queue timestamp.

Table 7: Average Wait Times Comparison for 9/21/2023 Visual vs. SMATS Cases

Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	0:15	0:06	-0:08	0:08	-0:06
06-08	0:31	0:13	-0:17	0:22	-0:08
08-10	1:21	0:31	-0:50	0:45	-0:35
10-12	1:49	0:30	-1:19	0:35	-1:14
12-14	0:41	0:54	+0:12	1:13	+0:31
14-16	0:21	0:05	-0:16	0:12	-0:09
16-18	0:18	0:16	-0:01	0:26	+0:08
18 ~	0:30	0:12	-0:17	0:17	-0:12

Day Avg.	1:01	0:22	-0:38	0:34	-0:26

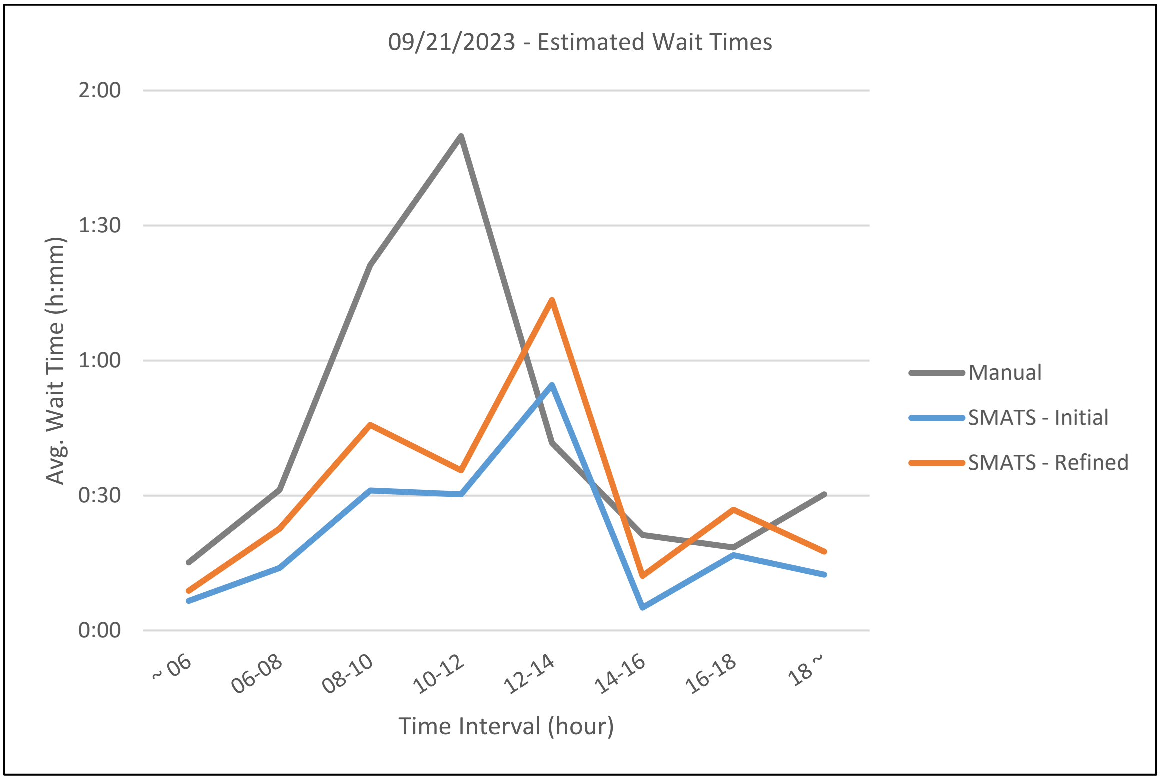


Figure 11: Average Wait Times Comparison for 9/21/2023 Visual vs. SMATS Cases

In several instances, both SMATS filter parameter cases seemed to have the greatest difficulty mirroring the visual wait time data specifically at the peak time intervals, as demonstrated in Table 8 & Figure 12 below (for estimated wait time figures of all days see Appendix E).

Table 8: Average Wait Times Comparison for 9/27/2023 Visual vs. SMATS Cases

Time Interval	Manual	SMATS - Initial		SMATS - Refined	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	1:02	0:08	-0:54	0:14	-0:47
06-08	0:24	0:14	-0:09	0:30	+0:05
08-10	1:20	0:28	-0:52	0:44	-0:35
10-12	2:19	0:30	-1:49	0:47	-1:32
12-14	1:55	0:47	-1:08	0:59	-0:55
14-16	1:23	0:52	-0:30	1:02	-0:20
16-18	0:32	0:09	-0:23	0:15	-0:17
18 ~	0:47	0:10	-0:37	0:12	-0:35
Day Avg.	1:26	0:30	-0:56	0:44	-0:42

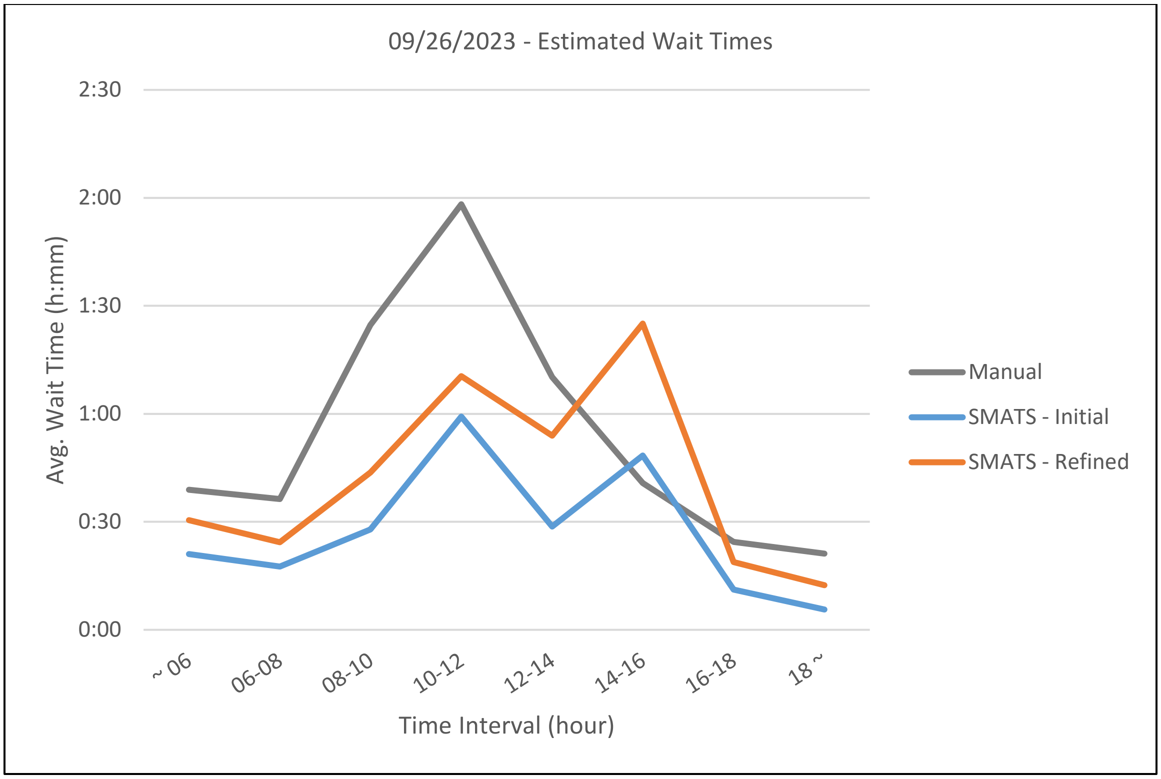


Figure 12: Average Wait Times Comparison for 9/27/2023 Visual vs. SMATS Cases

SMATS 90th Percentile Waiting Time Analysis

Along with comparing results from the different cases of filter parameter settings in the SMATS iNode^{TM} data, this research compared the 90th percentile average wait times of the manually validated data from the validation cameras to the 90th percentile average wait times of the initial and refined cases of SMATS iNode^{TM} data. The purpose of this comparison was to evaluate the effectiveness of the 90th-percentile analysis method in reducing the difference between the SMATS cases results from the manually validated results. As mentioned, the SMATS results were mostly underestimating the wait times and this could potentially be mitigated by using the 90th-percentile method to reduce the sample of lower-than-expected wait times in the SMATS result (see Figure 8).

One of the most crucial aspects of wait time analysis is correctly estimating the peak that the raw averages could struggle with. There was a significant improvement in the proximity of the SMATS results to the manual data for peak time period wait time estimations in some cases when using the 90th-percentile method, as shown in Figure 13 below.

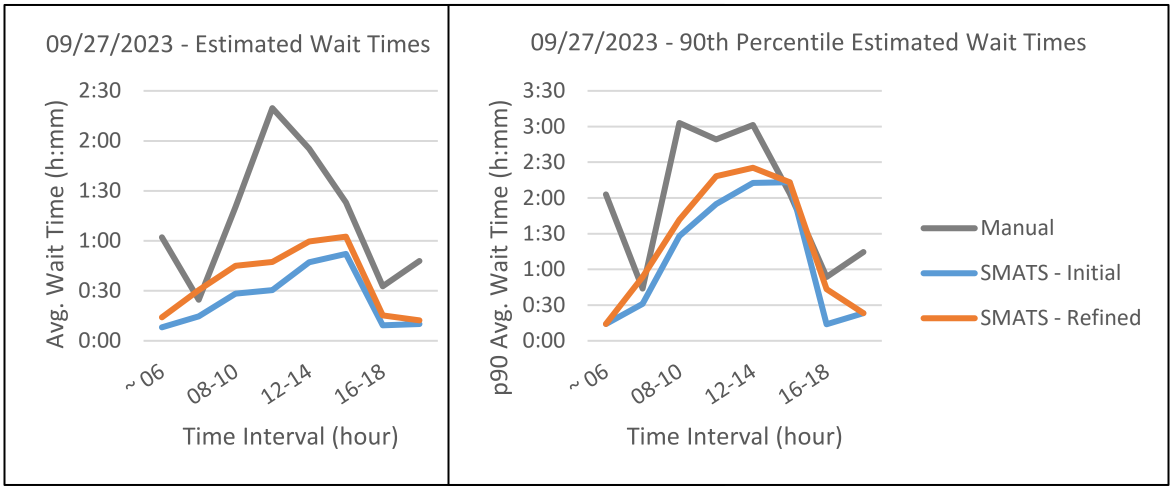


Figure 13: Raw Average vs. 90th Percentile Comparison - 9/27/2023

However, there were cases in which the 90th-percential method would overestimate the wait times of the SMATS results when compared to the manual results, as seen in the results of 9/21/2023 in Figure 14 below. This was a case where the peak average wait times of the SMATS results seemed to be offset time interval later than the manual results, which led to the overestimation that was exaggerated by the 90th-percentile method.

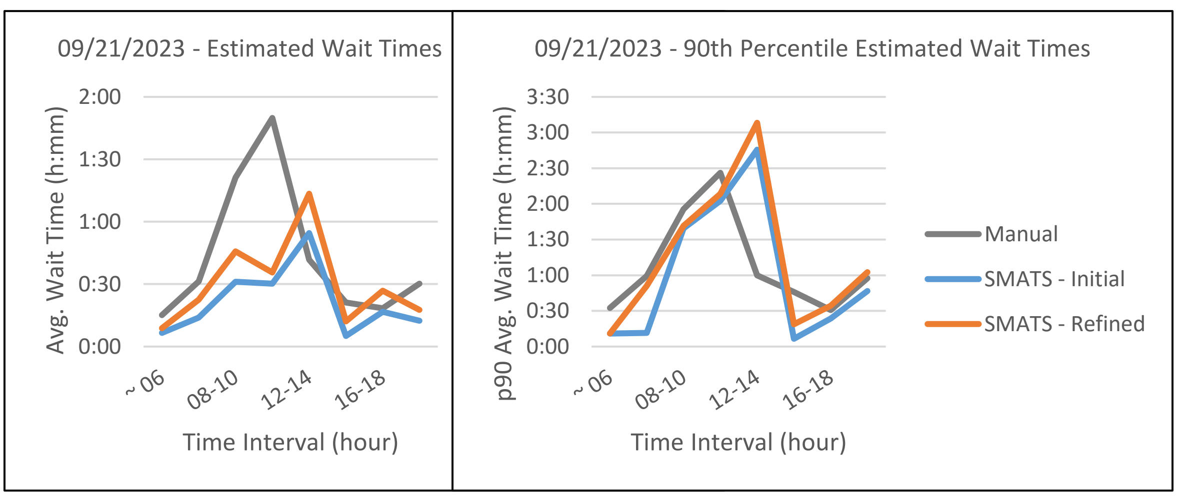


Figure 14: Raw Average vs. 90th Percentile Comparison - 9/21/2023

The exaggeration effects of the 90th-percentile method results seemed to be increased in the off-peak time intervals where ridership was lower and thus the sample size was lower, as seen in Figure 15 below. The lower sample size seemed to impact the SMATS results greater than the manual data as the SMATS data already had a smaller sample size to begin with than the manual data. With the much smaller samples, the 90th-percentile method allowed for outlier maximums to have a greater, or sole, influence on the average wait time reported.

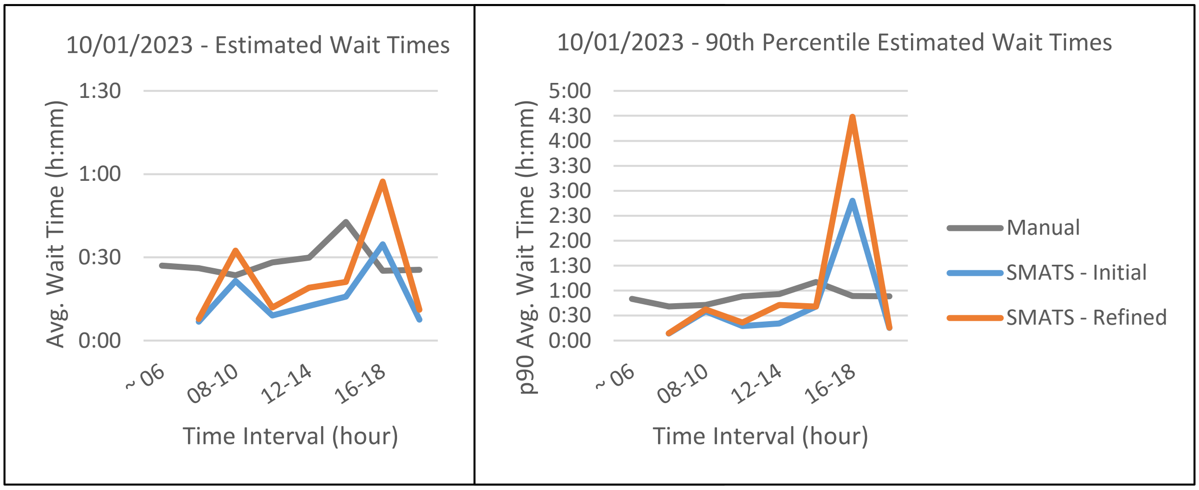


Figure 15: Raw Average vs. 90th Percentile Comparison - 10/01/2023

RESEARCH PRODUCTS AND RECOMMENDATIONS

The ferry system operated by the NCDOT caters to a wide range of people living on or visiting the eastern coast of the state. It covers routes tailored for daily commuters as well tourists. Unlike other public transportation modes, such as buses or trains, ferry routes have unique operational aspects. They are limited in the number of vehicles they can carry and are bound by specific sailing schedules, which unavoidably lead to queues and wait times. However, the ability to accurately measure and communicate these waiting times is currently not available for travelers using the ferry service. In practice, providing ferry users with information about wait times would enhance their overall 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.

The main problems that would need to be mitigated for the LPR technology would be the privacy concerns of storing license data, significant post-processing requirements, and high setup or maintenance costs. Otherwise, the tested LPR technologies have a larger sample size and more accurate wait time measurements than the tested Bluetooth devices. With the uncertainty of the ability or readiness of Google Maps to be utilized, it is recommended to apply internally owned and operated devices for a near-time solution with a future evaluation to assess the feasibility as appropriate.

Major findings from this research are presented below.

LPR Camera Performance

In terms of the performance of LPR camera, this research revealed that in a realistic setting the tested LPR camera was able to photograph approximately 80 percent of the entire population of vehicles that on-boarded the vessels from the dock that the camera was installed adjacent to. Among the photographed samples, the average LPR read rate was 86 percent. Though this research was unable to utilize multiple LPR cameras to determine the matching rate of this specific LPR camera model, the LPR camera performance assessment results proved that LPR technology is a reliable and robust approach to track and estimate waiting time at ferry terminals. The LPR cameras have consistently (from the initial research built on by this research (Yang, 2022) shown significantly higher capture rates than the alternative versions of Bluetooth/Wi-Fi sensors.

Through manual review and verification of the LPR images, this research summarizes several key factors that affect LPR camera performance, including but not limit to the following aspects:

LPR Camera Configuration

LPR cameras have very specific installation requirements. As such, the research team utilized remote assistance while installing the LPR camera from the helpful techs from the camera manufacturers to ensure that the right conditions were met and that the internal settings were calibrated correctly.

Plate Occlusion
This research compared the performance of the LPR camera with both vehicles where the license plate was occluded and free from any occlusions. Results show that the capture rate was 24 percent lower when the license plates were occluded to some extent. Since the LPR utilizes visual data to determine the contents of a license plate, it becomes more difficult to determine the entire contents accurately when parts of or whole characters are missing from the field-of- view.

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. During the data collection period for this research, variant plates were accurately read 9 percent less than standard plates. Variations in letter and number fonts, either between different states or countries of origin or custom plates, also affect LPR camera read rates. This is most evident in cases where the LPR system could not differentiate the similar characters such as the letter “O” and the letter “D” or the letter “B” and the number “8”.

Traffic Flow Condition
In addition to the previous three commonly recognized aspects, previous 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.

Bluetooth & Wi-Fi Sensor Performance
In terms of the performance of SMATS Bluetooth & Wi-Fi sensors, this research showed that in a realistic setting the sensors can potentially capture between 35 and 55 percent of the entire population of vehicles that queued for the ferry terminal. Though there was some variance between the visually validated wait times and the SMATS sensor data, there was enough correlation to suggest that the data collection procedures could be improved in time to strengthen the correlation and proximity to accurate wait time estimations.

One of the largest benefits of the system SMATS has in place with the sensors is that it is a mostly turn-key installation with an already developed system to match devices and calculate travel times/wait /times without the need to develop such methods.

The use of percentile filtering could have some promising effects to the SMATS data. However, there were cases were the percentile method was more detrimental and will report higher wait times than a raw average. It also is more difficult to do in real-time or at all as opposed to the manipulation of the filter parameter settings in the SMATS iNode^{TM} data.

Through manual review and verification of the validation videos and SMATS data, this research summarizes several key factors that affect the sensors performance, including but not limit to the following aspects:

Sample Size and Filter Parameters

Penetration rate is one of the typical weaknesses of Bluetooth & Wi-Fi, though with an increase in traffic (and subsequently increase in sample size) over the peak summer period when the wait time data is the most crucial, that there could be observed improvements in sensor performance in estimating wait times. An additional method of improvement the sampling of the sensors would be continued refinement of the post-processing filtering parameters.

Detection Area

The nature of the Bluetooth & Wi-Fi sensors detection is a blanket area instead of a specific point. This has the potential to cause difficulty pin-pointing vehicles that actually queue for and on-board the ferry vessels, as vehicles that are abandoning the queue or visiting neighboring destinations might be erroneously included in the sample of vehicles. This could potentially be mitigated by the use of direction antennas as opposed to the omnidirectional antennas used in this research, so as to create more controlled detection areas.

Automated Ferry Wait Time Notification System for NCDOT

We propose the implementation of an Automated Ferry Wait Time Notification System designed to offer accurate and timely updates on wait times for ferry ports managed by the North Carolina Department of Transportation (NCDOT). The core of this system is a SQL database that will store the necessary data, primarily, the ferry wait times. This data will be fed into the database through an automated or semi-automated process, which might involve an API client. Once the data is securely stored, the custom-developed script will be scheduled to retrieve the most recent wait time data from the database. This data retrieval will occur on a regular basis, with an initial setup providing updates every hour. The retrieved data can be disseminated through two primary channels: email or/and social media (such as the current usage of Twitter by the Ferry Division). For email notifications, this service will format the data into an easy-to-understand message and send it via a secure SMTP server to designated recipients. For social media updates, our service will similarly format the data into a tweet and post it through the Twitter API. One of the key features of the script is its flexibility. The frequency of data retrieval and notifications can be tailored to NCDOT's specific requirements. This allows for a balance between ensuring the recency of the information and avoiding an overload of messages.

Alternative Wait Metric

An alternative method of reporting wait time instead of estimated time in minutes could be to report estimated boarding intervals vehicles could be expecting to wait through. For example, “Refer to ferry schedule – expect board second ferry” or “Expected to board ferry departing at 3pm”. Of the two examples, the second would be the recommended format for reporting wait time in intervals of ferry departures due the clarity of messaging instead of relying on the customers to determine the ferry schedule for themselves to determine when they could expect to depart and how long they may have to wait.

Future Research

The alternative wait time metric mentioned above of number of ferry sailings or estimated departure time lends the assessment of wait time to focus less on individual vehicles and more so on the overall capacity and customer demand on the ferry terminal at a given time. This perspective on wait-time analysis leads the research team to suggest that utilizing a high-mounted static camera could allow for the use of an AI detection algorithm (either proprietary or internally developed) for the use in estimating wait times. The total vehicles queued could be counted at intervals along with the ferry vessels' schedules and capacity to determine the estimated wait. This could be a potentially advantageous solution for cost and effectiveness.

Study Limitations

Due to the scheduling constraints to have the temporary access to both devices tested (Vidar LPR and SMATS Bluetooth & Wi-Fi) coincide with each other, the data collection period was not able to take place during the peak traffic of the summer, when the information provided by a potential wait-time-sharing system would be the most crucial. It is unknown at this time how the increase in sample size would impact the devices.

REFERENCES

Adaptive Recognition. *Vidar Camera*. Available: https://adaptiverecognition.com/products/vidar-anpr-camera/ (Accessed: April 11, 2024)

Andersen S. N., Tørset, T. (2019). Waiting time for ferry services: Empirical evidence from Norway. *Case Studies on Transport Policy*. Vol 7, pp. 667-676.

Bert, S., Norboge, N., Davis, J., Head, W., Babich, J., Findely, D. *Economic Contribution of North Carolina's Ferry System*. Report No. NCDOT-87727, North Carolina Department of Transportation, Raleigh, 2020.

Chang, S.L., Chen, L.S., Chung, Y.C., Chen, S.W. Automatic License Plate Recognition. *IEEE Transactions on Intelligent Transportation Systems*, Vol.5(1), 2004, pp.42-53, DOI: 10.1109/TITS.2004.825086

Díez-Gutiérrez, M., Tørset, T. Perception of inconvenience costs: Evidence from seven ferry services in Norway. *Transport Policy*, Vol.77, 2019, pp.58-67.

Dion, Francois, and Hesham Rakha. "Estimating Dynamic Roadway Travel Times using automatic vehicle identification data for low sampling rates." Transportation Research Part B: Methodological, vol. 40, no. 9, Nov. 2006, pp. 745–766, https://doi.org/10.1016/j.trb.2005.10.002.

Findley, D.J., Anderson, T.J., Bert, S.A., Nye, T., Letchworth, W. (2018). Evaluation of Wait Times and Queue Lengths at Ferry Terminals, *Research in Transportation Economics*, Vol. 71, pp. 27-33.

Findley, D.J., Cunningham, C.M., Chang, J.C., Hovey K.A., Corwin, M.A. Effects of License Plate Attributes on Automatic License Plate Recognition. *Transportation Research Record*, No.2327, 2013, pp. 34–44.

Li, Matthew. "Understanding the Measures of Bluetooth RSSI." MOKOBlue, MOKOSMART, 16 Mar. 2023, www.mokoblue.com/measures-of-bluetooth-rssi/#:~:text=An%20ideal%20RSSI%20value%20of,number%20illustrates%20a%20better%20connection.

Maister, D.H. *The psychology of waiting lines*. In: John A. Czepiel M. R, Solomon , and Surprenant Carol F., eds. The Service Encounter, Lexington, MA: Lexington Books, 1985. pp.113-124.

NCDOT. *The North Carolina Ferry Division*. https://www.nc.gov/agency/ferry-division#:~:text=The%20North%20Carolina%20Ferry%20Division,2%20million%20passengers%20a%20year. (Accessed: May 13, 2021)

NCGA. *Reducing Off-Season Crossings, Adjusting Fares, and Using Partnerships Can Improve Ferry Division Efficiency*. Report Number 2017-09, North Carolina General Assembly, Raleigh, NC, 2017.

SMATS. *Travel Time Sensors Technology*. Available: https://www.smatstraffic.com/travel-time-sensors/ (Accessed: April 11, 2024)

Yang, Guangchaun, et al. 2022, Investigation of Wait Time Technology for the Ferry System, https://connect.ncdot.gov/projects/research/Pages/ProjDetails.aspx?ProjectID=2020-34.

APPENDICES

Appendix A: Adaptive Recognition Vidar LPR Camera Data Sheet

ADAPTIVE RECOGNITION

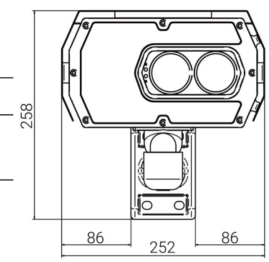
Technical Datasheet

Vidar – ANPR/ALPR cameras for traffic monitoring

On-Board ANPR+MMR, powered by:

CARMEN®

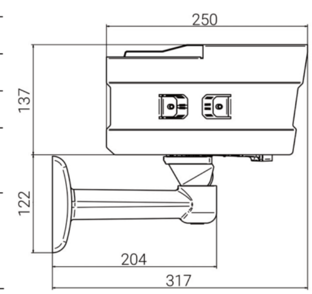
Imaging	Vidar HDx	Vidar Smart HDx	Vidar Smart 2xHDx LT	Vidar Smart 2xFHDx LT	Vidar Smart 5MpHDx LT
Resolution	1440 x 1080		Sensor 1&2: 1440×1080	Sensor 1&2: 2048×1536	Sensor 1: 2432×2048 Sensor 2: 1440×1080
Max FPS	120 @ 720p		120 @ 720p	60 @ 1080p	45 @ 3MP on sensor 1 or 120 @ 720p on sensor 2
Sensor	Color, Global Shutter		Sensor 1&2: Color, Global Shutter		
Day/Night switch	Automatic brightness control with predefined traffic environments or manual				
Lens	Motorized zoom and focus, remotely adjustable				
Lens mount	Custom mount				
Angle of View	Wide: 55.7° x 43.2° Tele: 3.4° x 2.5°		Optics 1&2: Wide: 55.7° x 43.2° Tele: 3.4° x 2.5°	Optics 1&2: Wide: 26.5° x 20° Tele: 8.1° x 6.1°	Optics 1: Wide 25.1°×21.3° Tele: 7.7° × 6.4° Optics 2: Wide: 55.7° × 43.2° Tele: 3.4° x 2.5°
Optical Zoom	18×		Optics 1&2: 18×	Optics 1&2: 3.3×	Optics 1: 3.3× Optics 2: 18×
Focal length	Variable 4.8 – 84.6 mm		Optics 1&2: Variable 4.8 – 84.6 mm	Optics 1&2: Variable 15 – 50 mm	Optics 1: Variable, 15 – 50 mm Optics 2: Variable, 4.8 – 84.6 mm



Distance ANPR Range

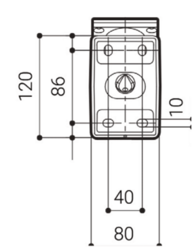
Optimal ANPR range at ambient light	4 m – 20 m (13 feet – 65 feet)	10 m – 20 m (33 feet – 65 feet)	
Maximal ANPR range at optimal conditions	50 m (164 feet)	40 m (131 feet)	50 m (164 feet)
Maximum ANPR range at "0" lux*	35 m (115 feet)		
Vehicle speed range (at optimal conditions)	0 km/h – 320+ km/h / 0 mph – 199+ mph		
Maximum road width covered (at standard license plate size)	6 m (20 feet)	8 m (26 feet)	10 m (33 feet)

* In the case of reflective license plates



On-Board Intelligence

Carmen on-board ANPR	–	✓	✓	✓	✓
ANPR Cloud compliant	soon	soon	soon	soon	soon
GDS compliant	✓	✓	✓	✓	✓
MMR + Color	–	✓	✓	✓	✓
Vehicle category	–	✓	✓	✓	✓
Video analytics	Image preselection (license plate detection)	License plate detection, vehicle direction detection, vehicle category			
ADR Recognition	–	✓	✓	✓	✓



3-year warranty
Made in EU

CE FC UL RoHS ONVIF

Technical specifications are subject to change without prior notice. This document does not constitute an offer

requestinfo@adaptiverecognition.com
www.adaptiverecognition.com

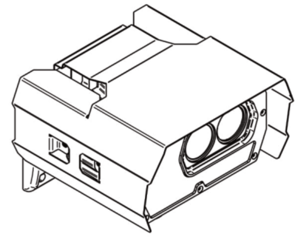
• dual motorized optics • high-performance 4-core ANPR processor • built-in laser trigger • MMR + color • up to 120 FPS on selected models • reads reflective/non-reflective plates simultaneously • overview lens • direction detection • wealth of features • 850 nm IR illumination • spectacular night-time performance • natively GDS-ready • vehicle categorization

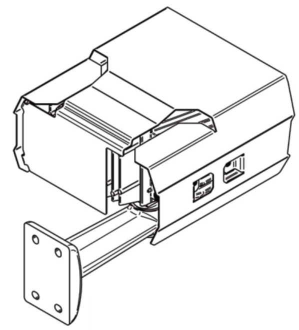
Release date: 07. 06. 2023

ADAPTIVE RECOGNITION

Technical Datasheet

Vidar – ANPR/ALPR cameras for traffic monitoring





Illumination

Illumination	Vidar HDx	Vidar Smart HDx	Vidar Smart 2xHDx LT	Vidar Smart 2xFHDx LT	Vidar Smart 5MpHDx LT
Wavelength	850 nm*				
Illumination modes	Synchronized or continuous				
Illumination beam-angle	22°				
Variable intensity	Adjustable in 100 increments, parity flash (different intensity for odd and even frames)				

*Other Vidar models are available with 760 nm (near infrared) and white built-in illumination as well

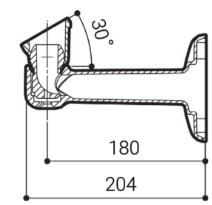
Processing & I/O

Processing & I/O	Vidar HDx	Vidar Smart HDx	Vidar Smart 2xHDx LT	Vidar Smart 2xFHDx LT	Vidar Smart 5MpHDx LT
ANPR Processing unit	–	ARM 64-bit Quad-Core @ 1.4 GHz			
Communication protocols	ONVIF, ARP, TCP/IP, DHCP, NTP, FTP, HTTP, RTSP, HTTPs, SFTP (Smart models only), DNS, SNMP, SSL/TLS, NTCIP				
I/O ports	12-pin (UART/GPIO/USB/RS232)				
In-built Laser Trigger	–	–	8 mRad Point Laser		
Laser wavelength & safety class	–	–	905 nm CLASS 1 (60825-1 2014)		
Radar for triggering	–	–	–	Optional, 4D MultiLane Radar	
Certified vehicle speed data	–	–	–	Optional	Optional

Storage

Storage	Vidar HDx	Vidar Smart HDx	Vidar Smart 2xHDx LT	Vidar Smart 2xFHDx LT	Vidar Smart 5MpHDx LT
Internal storage size and type	–	32 GB* SSD			
Stored number of events (Internal)**	–	approx. 90000	approx. 90000	approx. 50000	approx. 40000
Event package size for external upload**	~ 200 kB	250 - 400 kB	250 - 400 kB	350 - 500 kB	400 - 550 kB
External storage type	FTP, HTTP, SMTP	FTP, SFTP, HTTP, HTTPS	FTP, SFTP, HTTP, HTTPS	FTP, SFTP, HTTP, HTTPS	FTP, SFTP, HTTP, HTTPS

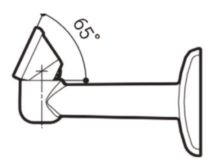
* Internal storage: max. 1 TB SSD (available upon request)
**With default settings



Electrical Data

Electrical Data	Vidar HDx	Vidar Smart HDx	Vidar Smart 2xHDx LT	Vidar Smart 2xFHDx LT	Vidar Smart 5MpHDx LT
Power requirement	24 - 28 V AC*; min. 2A		24 - 28 V AC*; min. 2.5A		
Typical power consumption	11 W	18 W	20 W	20 W	20 W
Maximum power consumption	30 W	50 W	60 W	60 W	65 W

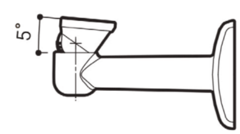
*36 V DC when a common ground is used with external illuminator



Mechanical Data

Mechanical Data	Vidar HDx	Vidar Smart HDx	Vidar Smart 2xHDx LT	Vidar Smart 2xFHDx LT	Vidar Smart 5MpHDx LT
Operating temperature*	-45°C – +70°C (-49°F - +158°F)				
IP&IK rating	IP67, IK10 (additional accessory component required)				
Dimensions with bracket (L×W×H)	250 x 252 x 258 mm / 9.84" × 9.92" × 10.16"				
Weight	4.5 kg / 9.92 lbs				
In the box	Camera, bracket, shield				

*Internal



Accessories

M12 power cable, Ethernet cable, I/O Cable, 4D MultiLane Radar, Junction Box, External IR-light

Certificate

Made in EU, NDAA compliant

3-year warranty
Made in EU

Technical specifications are subject to change without prior notice. This document does not constitute an offer

requestinfo@adaptiverecognition.com
www.adaptiverecognition.com

• dual motorized optics • high-performance 4-core ANPR processor • built-in laser trigger • MMR + color • up to 120 FPS on selected models • reads reflective/non-reflective plates simultaneously • overview lens • direction detection • wealth of features • 850 nm IR illumination • spectacular night-time performance • natively GDS-ready • vehicle categorization

Release date: 07. 06. 2023

Appendix B: SMATS TRAFFICBOX™ Data Sheet

SMATS

Technical Specifications

TrafficXBox™

Item	Value
Operating temperature	-40°C~75°C
Dimension	401 x 307 x 172mm (15.8 × 12.1 × 6.8″ inches)
Weight	1.8 Kg
Mean time between failures (MTBF)	100,000 hours
	5 V or 12 V Battery pack
Power Consumption	Typical <4 W with GSM without Wi-Fi
	Typical <6 W with GSM with Wi-Fi
Bluetooth Module Classic	Class 1
	+18dBm TX power, -90dBm RX Sensitivity
Bluetooth Module Low Energy	+4dBm TX power (Max), -96dBm RX Sensitivity
Bluetooth Module Paired Mode	-98 RX Sensitivity
Wi-Fi Module	802.11 b/g/n
	-92dBm RX Sensitivity
Processor	Quad Core 1.2 GHz
RAM	1 GB SD
Memory Capacity	> 400 million MAC records
Storage	16 GB SD Card
Antennas	Omnidirectional
	Bluetooth and Wi-Fi: 2400 MHz, 1.5, 2 dBi gain options, IP65
Operating System	Linux 3.1
Enclosure	IP68
GPS	SiRF Start 4, -163dBm tracking sensitivity, 48 Track channels
Cellular Modem	LTE: North America (B2, B4, B5, B17) Europe (B1, B3, B7, B8, B20)
Available Ports	Ethernet
	USB (2 ports)
RF Compliance	FCC,IC Compliant

Web. www.smatstraffic.com/T. 888 441 5666/E. info@smats.ca

Appendix C: SMATS iNode™ - Initial Case Filter Parameters

Link Config

Link Name	Ferry Wait-Time
Note	
Active Data Source	☑ ☑ Sensor
Live Data Source	☑ ☑ Sensor
Default Data Source	Sensor
Origin	Sensor 1
Destination	Sensor 2
Traffic Type	Public
Free Flow Speed(km/h)	40
Sensor: Update Interval	10 (min)

Live Data Matching Parameters

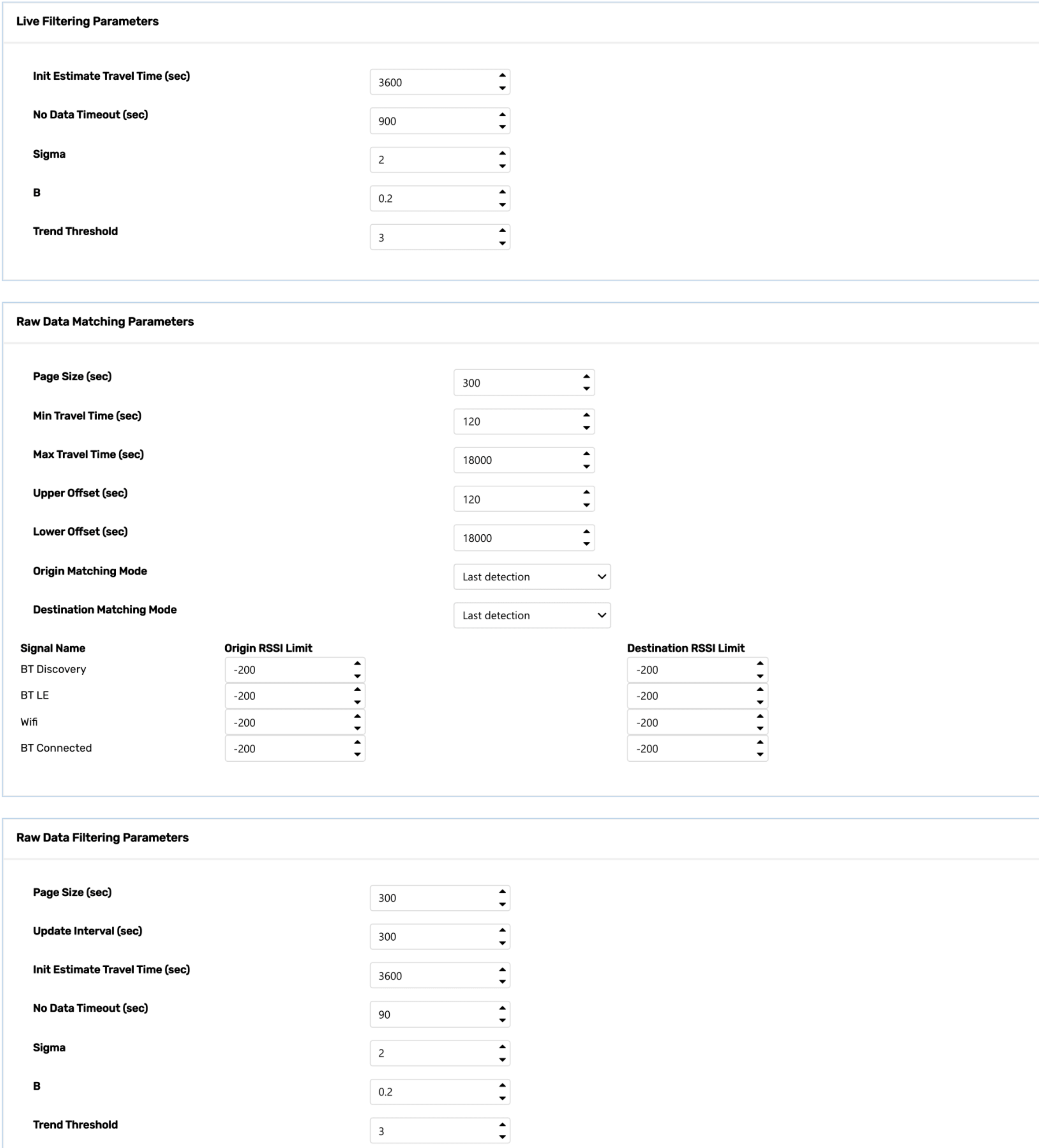
Auto Calculate

Min Travel Time (sec)	120
Max Travel Time (sec)	18000
Upper Offset (sec)	120
Lower Offset (sec)	18000
Origin Matching Mode	Last detection
Destination Matching Mode	Last detection

Signal Name	**Origin RSSI Limit**	**Destination RSSI Limit**
BT Discovery	-200	-200
BT LE	-200	-200
Wifi	-200	-200
BT Connected	-200	-200

Live Filtering Parameters

Init Estimate Travel Time (sec)	3600
No Data Timeout (sec)	900
Sigma	2
B	0.2
Trend Threshold	3


Live Filtering Parameters
Init Estimate Travel Time (sec)
3600
No Data Timeout (sec)
900
Sigma
2
B
0.2
Trend Threshold
3
Raw Data Matching Parameters
Page Size (sec)
300
Min Travel Time (sec)
120
Max Travel Time (sec)
18000
Upper Offset (sec)
120
Lower Offset (sec)
18000
Origin Matching Mode
Last detection
Destination Matching Mode
Last detection
Signal Name
Origin RSSI Limit
Destination RSSI Limit
BT Discovery
-200
-200
BT LE
-200
-200
Wifi
-200
-200
BT Connected
-200
-200
Raw Data Filtering Parameters
Page Size (sec)
300
Update Interval (sec)
300
Init Estimate Travel Time (sec)
3600
No Data Timeout (sec)
90
Sigma
2
B
0.2
Trend Threshold
3

Appendix D: SMATS iNode™ - Refined Case Filter Parameters

Link Config

Link Name	Ferry Wait-Time
Note	
Active Data Source	☑ ☑ Sensor
Live Data Source	☑ ☑ Sensor
Default Data Source	Sensor
Origin	Sensor 1
Destination	Sensor 2
Traffic Type	Public
Free Flow Speed(km/h)	40
Sensor: Update Interval	10 (min)

Live Data Matching Parameters Auto Calculate

Min Travel Time (sec)	120
Max Travel Time (sec)	18000
Upper Offset (sec)	120
Lower Offset (sec)	18000
Origin Matching Mode	Last detection
Destination Matching Mode	Last detection

Signal Name	**Origin RSSI Limit**	**Destination RSSI Limit**
BT Discovery	-200	-200
BT LE	-200	-200
Wifi	-200	-200
BT Connected	-200	-200

Live Filtering Parameters

Init Estimate Travel Time (sec)	3600
No Data Timeout (sec)	900
Sigma	2
B	0.2
Trend Threshold	3

Raw Data Matching Parameters

Page Size (sec)	300
Min Travel Time (sec)	300
Max Travel Time (sec)	18000
Upper Offset (sec)	300
Lower Offset (sec)	18000
Origin Matching Mode	Last detection
Destination Matching Mode	Last detection

Signal Name	**Origin RSSI Limit**	**Destination RSSI Limit**
BT Discovery	-200	-90
BT LE	-200	-90
Wifi	-200	-90
BT Connected	-200	-90

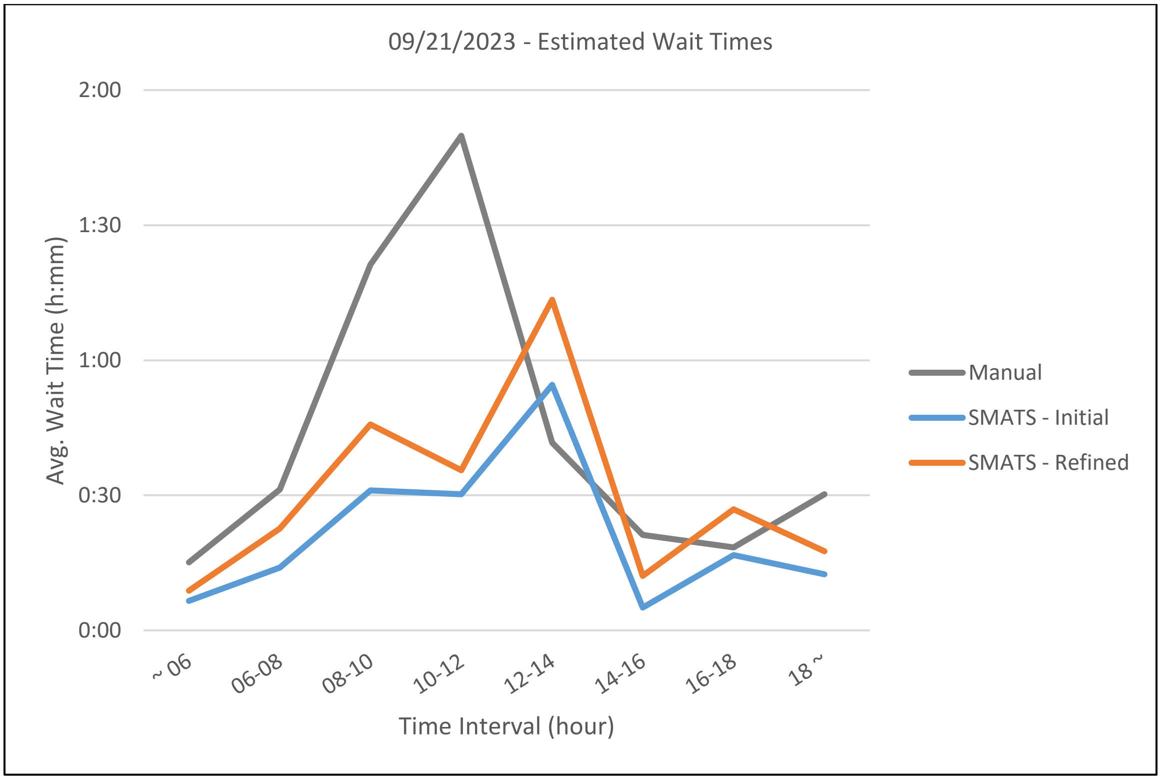
Raw Data Filtering Parameters

Page Size (sec)	300
Update Interval (sec)	300
Init Estimate Travel Time (sec)	3600
No Data Timeout (sec)	90
Sigma	2
B	0.2
Trend Threshold	3

Appendix D: Daily Estimated Wait Time Comparisons (Visual vs. SMATS Cases)

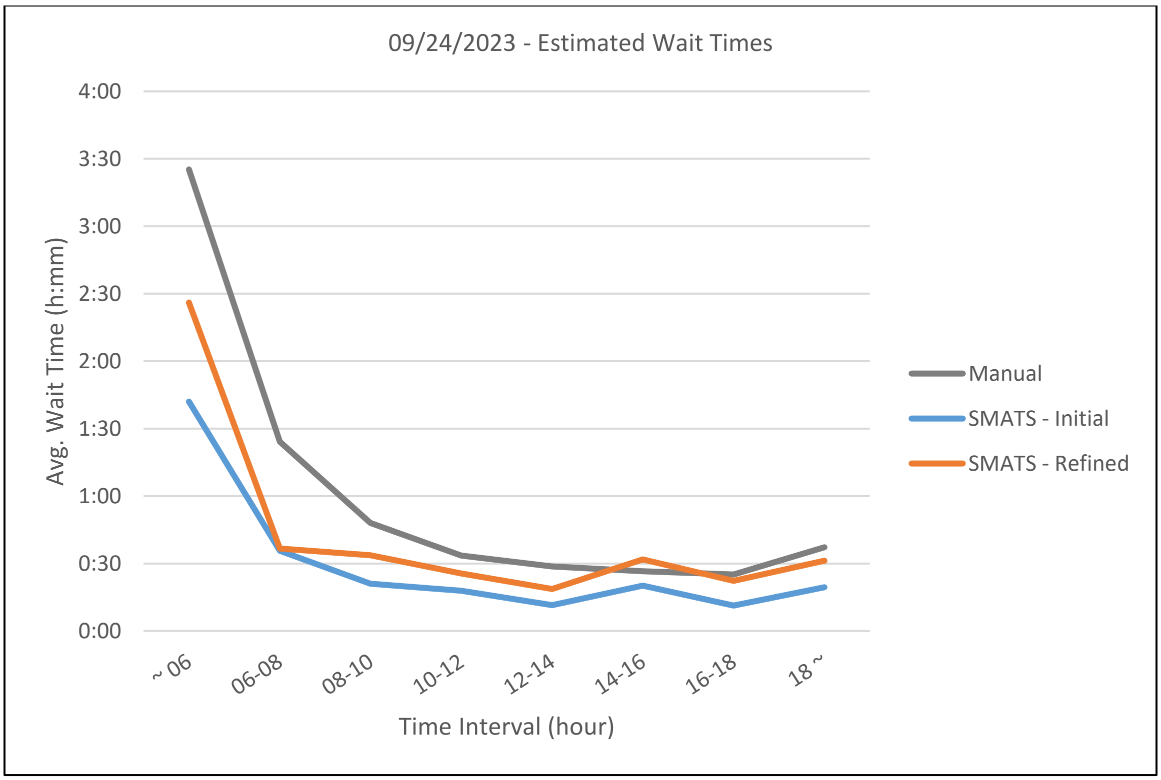
Average Wait Times Comparison for 9/21/2023 Visual vs. SMATS Cases

09/21/2023 Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	0:15	0:06	-0:08	0:08	-0:06
06-08	0:31	0:13	-0:17	0:22	-0:08
08-10	1:21	0:31	-0:50	0:45	-0:35
10-12	1:49	0:30	-1:19	0:35	-1:14
12-14	0:41	0:54	+0:12	1:13	+0:31
14-16	0:21	0:05	-0:16	0:12	-0:09
16-18	0:18	0:16	-0:01	0:26	+0:08
18 ~	0:30	0:12	-0:17	0:17	-0:12
Day Avg.	1:01	0:22	-0:38	0:34	-0:26



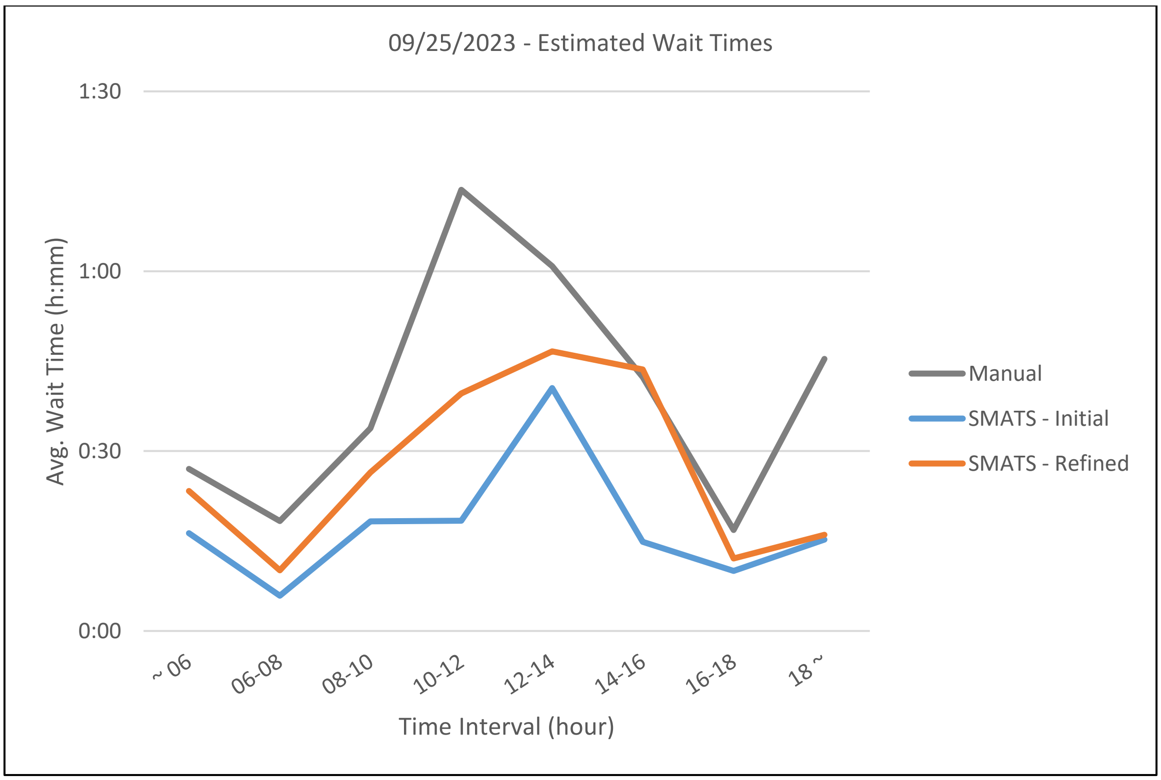
Average Wait Times Comparison for 9/24/2023 Visual vs. SMATS Cases

09/24/2023 Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	3:25	1:42	-1:43	2:26	-0:59
06-08	1:24	0:35	-0:48	0:36	-0:47
08-10	0:47	0:20	-0:26	0:33	-0:14
10-12	0:33	0:17	-0:15	0:25	-0:07
12-14	0:28	0:11	-0:17	0:18	-0:09
14-16	0:26	0:20	-0:06	0:31	+0:05
16-18	0:25	0:11	-0:13	0:22	-0:02
18 ~	0:37	0:19	-0:17	0:31	-0:06
Day Avg.	0:42	0:21	-0:21	0:33	-0:08



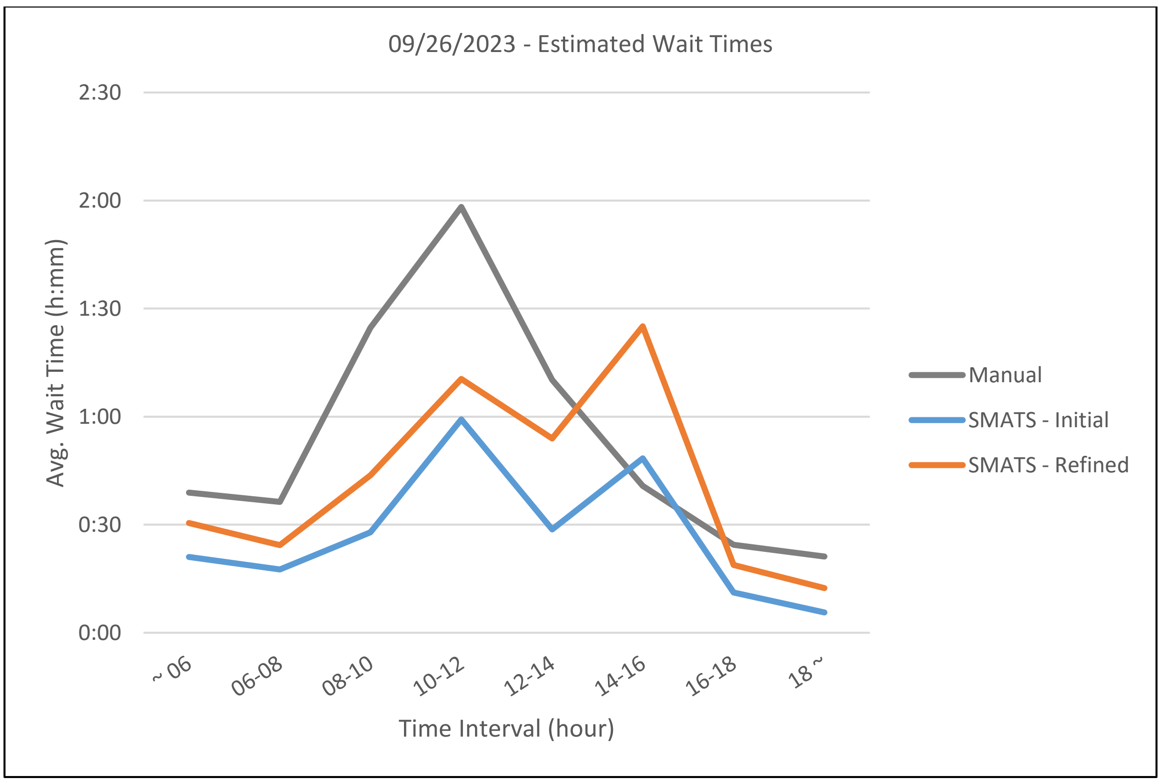
Average Wait Times Comparison for 9/25/2023 Visual vs. SMATS Cases

09/25/2023 Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	0:27	0:16	-0:10	0:23	-0:03
06-08	0:18	0:05	-0:12	0:10	-0:08
08-10	0:33	0:18	-0:15	0:26	-0:07
10-12	1:13	0:18	-0:55	0:39	-0:33
12-14	1:00	0:40	-0:20	0:46	-0:14
14-16	0:42	0:14	-0:27	0:43	+0:01
16-18	0:16	0:10	-0:06	0:12	-0:04
18 ~	0:45	0:15	-0:30	0:16	-0:29
Day Avg.	0:47	0:17	-0:29	0:29	-0:18



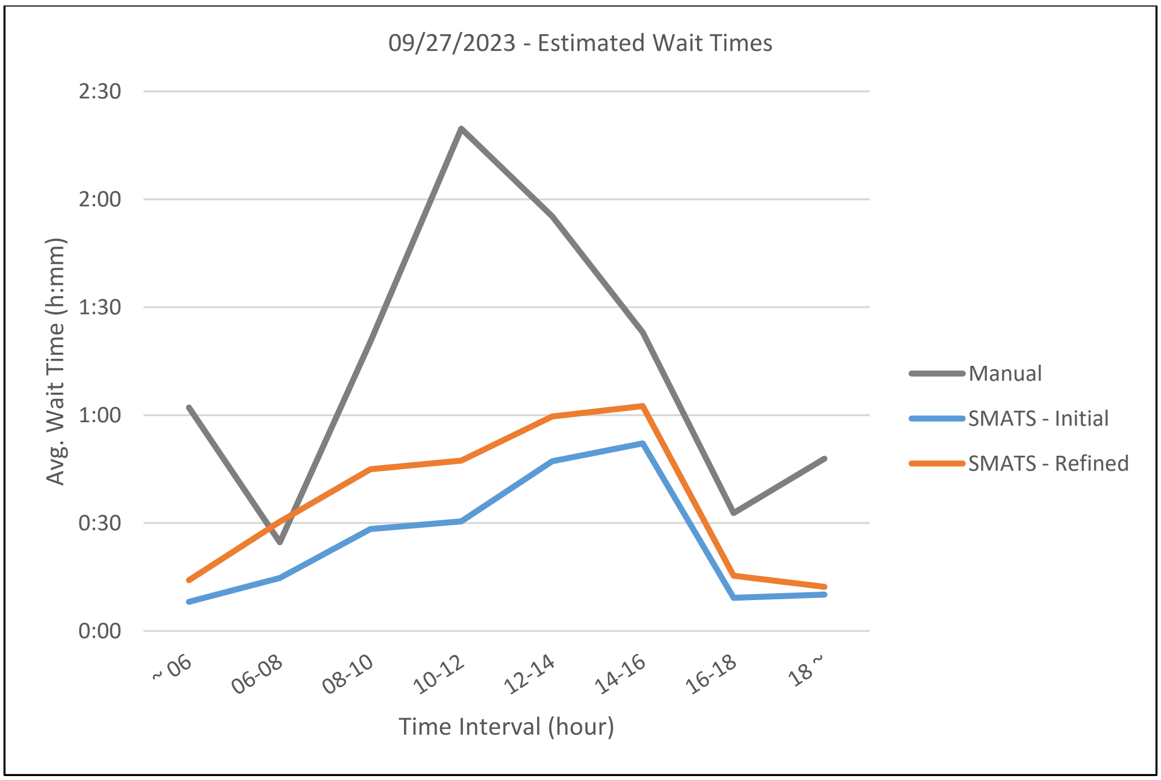
Average Wait Times Comparison for 9/26/2023 Visual vs. SMATS Cases

09/26/2023 Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	0:38	0:21	-0:17	0:30	-0:08
06-08	0:36	0:17	-0:18	0:24	-0:11
08-10	1:24	0:27	-0:56	0:43	-0:40
10-12	1:58	0:59	-0:58	1:10	-0:47
12-14	1:10	0:28	-0:41	0:53	-0:16
14-16	0:40	0:48	+0:07	1:25	+0:44
16-18	0:24	0:11	-0:13	0:18	-0:05
18 ~	0:21	0:05	-0:15	0:12	-0:08
Day Avg.	1:08	0:30	-0:38	0:46	-0:22



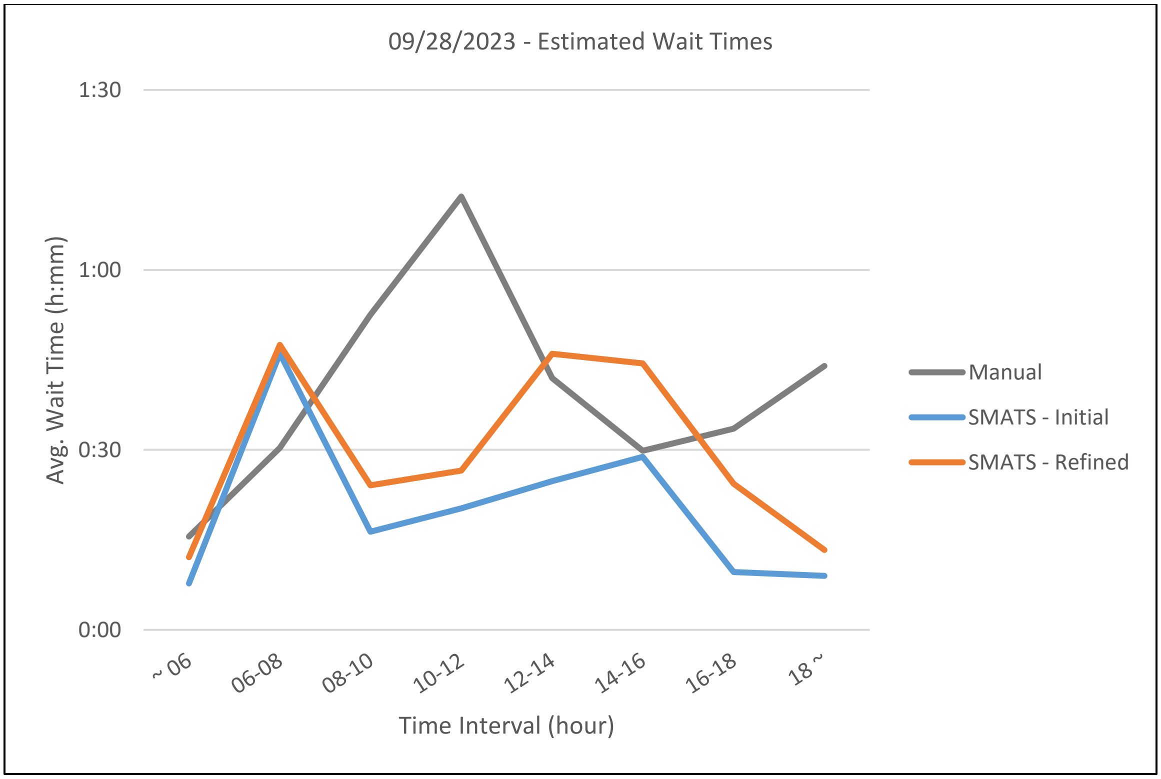
Average Wait Times Comparison for 9/27/2023 Visual vs. SMATS Cases

09/27/2023 Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	1:02	0:08	-0:54	0:14	-0:47
06-08	0:24	0:14	-0:09	0:30	+0:05
08-10	1:20	0:28	-0:52	0:44	-0:35
10-12	2:19	0:30	-1:49	0:47	-1:32
12-14	1:55	0:47	-1:08	0:59	-0:55
14-16	1:23	0:52	-0:30	1:02	-0:20
16-18	0:32	0:09	-0:23	0:15	-0:17
18 ~	0:47	0:10	-0:37	0:12	-0:35
Day Avg.	1:26	0:30	-0:56	0:44	-0:42



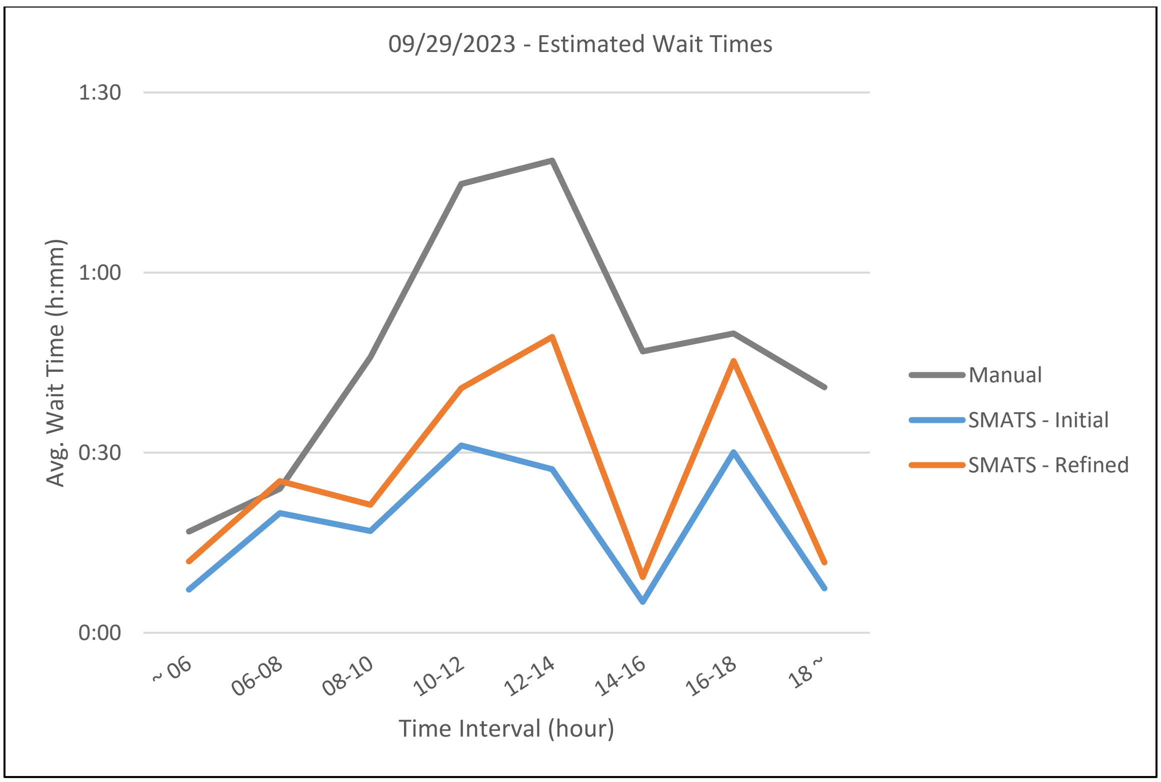
Average Wait Times Comparison for 9/28/2023 Visual vs. SMATS Cases

09/28/2023 Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	-	0:07	-	0:12	-
06-08	0:15	0:46	+0:30	0:47	+0:31
08-10	0:30	0:16	-0:13	0:24	-0:06
10-12	0:52	0:20	-0:32	0:26	-0:26
12-14	1:12	0:24	-0:47	0:46	-0:26
14-16	0:41	0:28	-0:13	0:44	+0:02
16-18	0:29	0:09	-0:20	0:24	-0:05
18 ~	0:33	0:09	-0:24	0:13	-0:20
Day Avg.	0:43	0:18	-0:25	0:28	-0:15



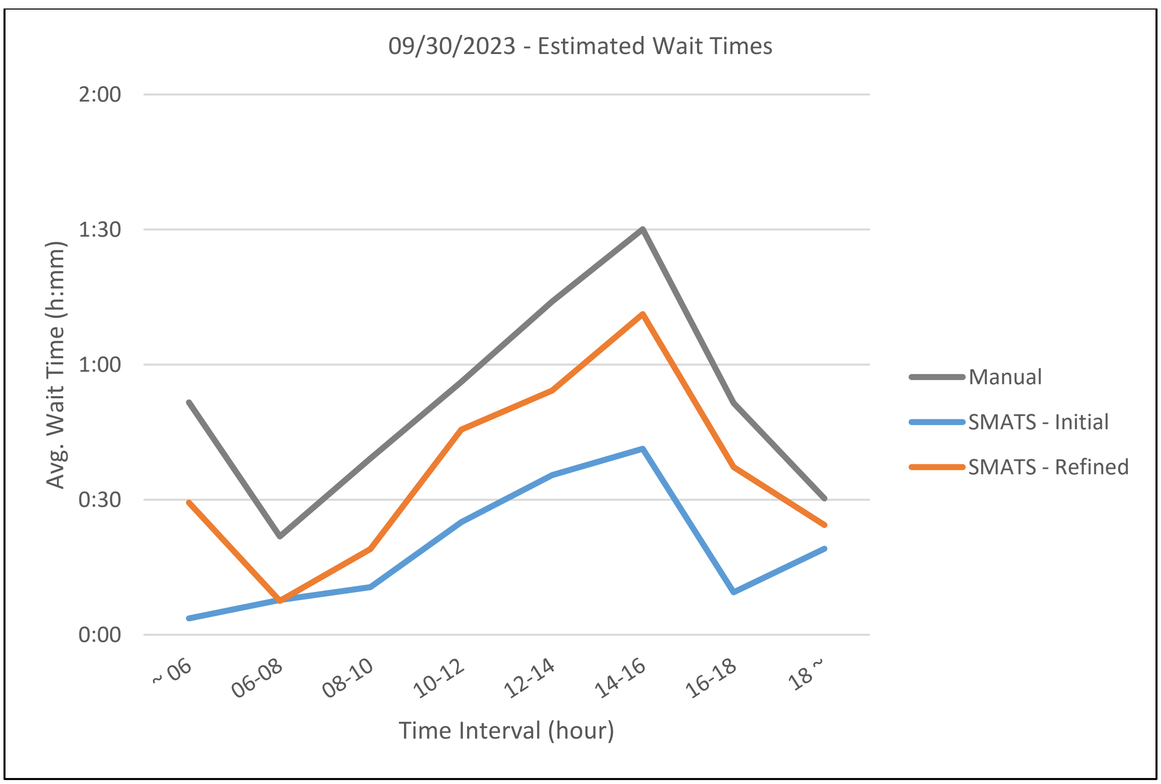
Average Wait Times Comparison for 9/29/2023 Visual vs. SMATS Cases

09/29/2023 Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	0:16	0:07	-0:09	0:11	-0:04
06-08	0:24	0:19	-0:04	0:25	+0:01
08-10	0:45	0:16	-0:28	0:21	-0:24
10-12	1:14	0:31	-0:43	0:40	-0:34
12-14	1:18	0:27	-0:51	0:49	-0:29
14-16	0:46	0:05	-0:41	0:09	-0:37
16-18	0:49	0:30	-0:19	0:45	-0:04
18 ~	0:40	0:07	-0:33	0:11	-0:29
Day Avg.	0:55	0:19	-0:35	0:28	-0:27



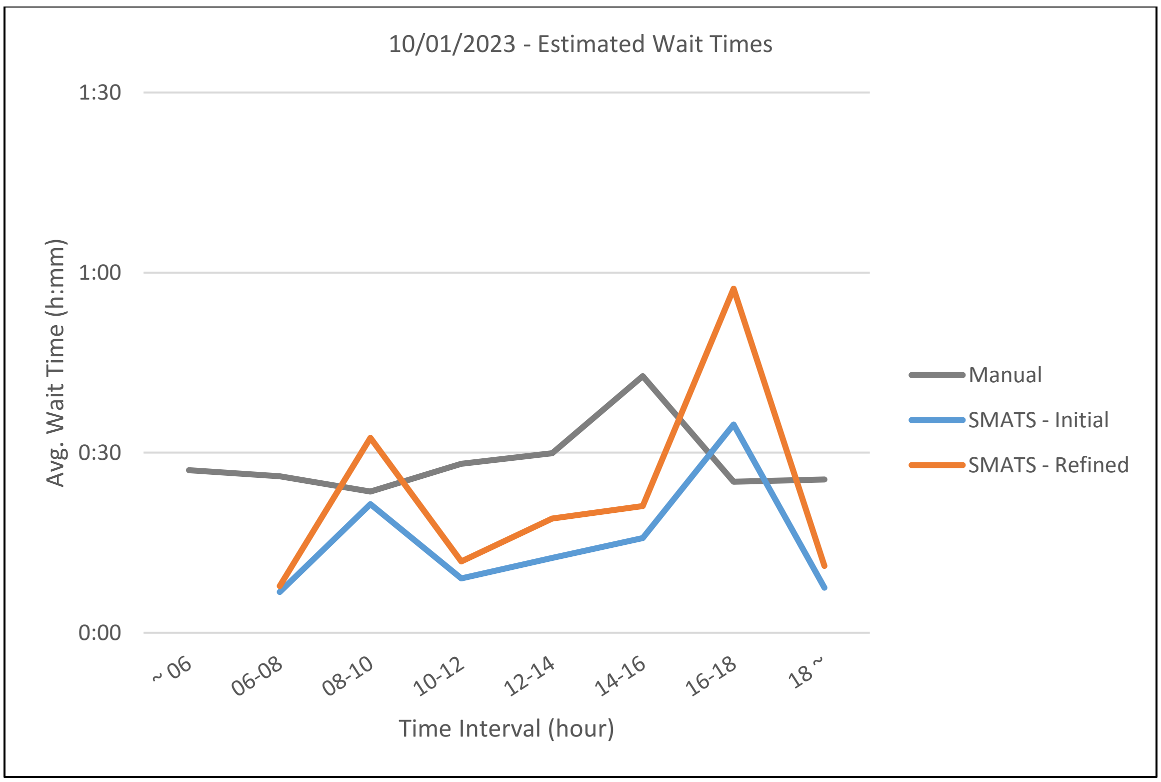
Average Wait Times Comparison for 9/30/2023 Visual vs. SMATS Cases

09/30/2023 Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	0:51	0:03	-0:48	0:29	-0:22
06-08	0:21	0:07	-0:14	0:07	-0:14
08-10	0:39	0:10	-0:28	0:19	-0:20
10-12	0:56	0:25	-0:31	0:45	-0:10
12-14	1:13	0:35	-0:38	0:54	-0:19
14-16	1:30	0:41	-0:48	1:11	-0:18
16-18	0:51	0:09	-0:42	0:37	-0:14
18 ~	0:30	0:19	-0:11	0:24	-0:05
Day Avg.	0:58	0:23	-0:35	0:37	-0:20



Average Wait Times Comparison for 10/01/2023 Visual vs. SMATS Cases

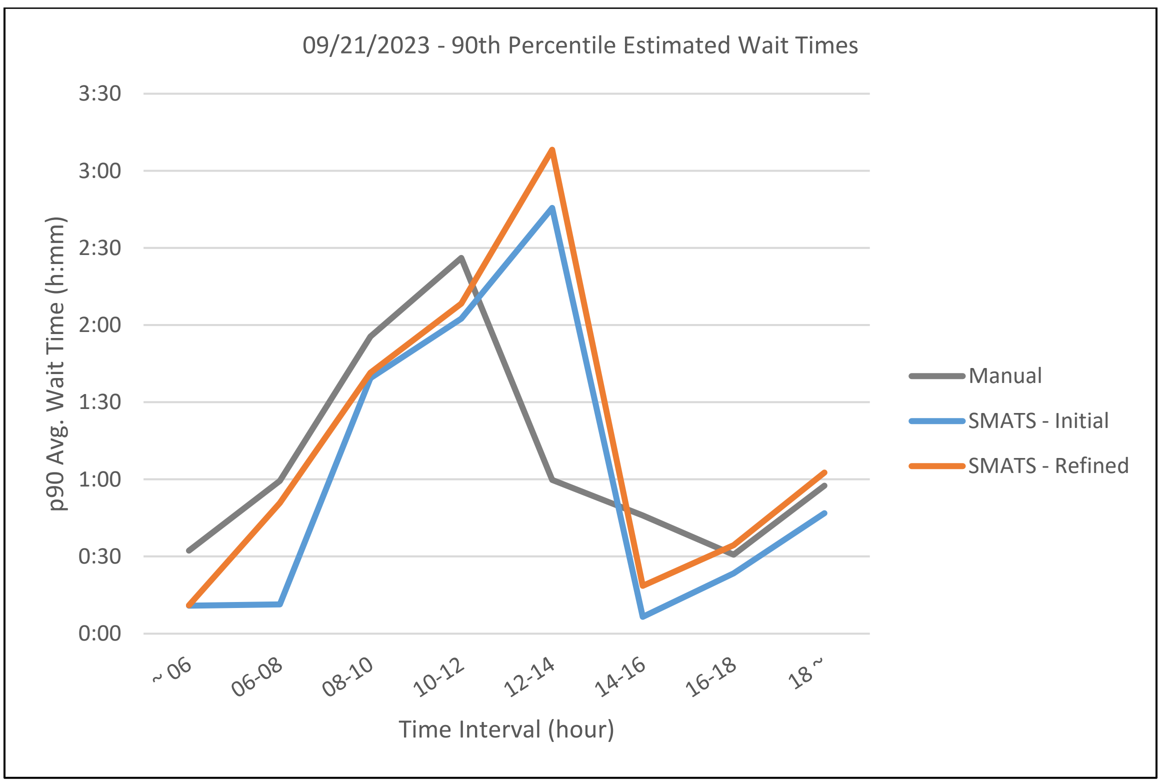
10/01/2023 Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	Avg. Wait Time	*Avg. Wait Time*	*Diff. from Visual*	*Avg. Wait Time*	*Diff. from Visual*
~ 06	0:27	-	-	-	-
06-08	0:26	0:06	-0:19	0:07	-0:18
08-10	0:23	0:21	-0:02	0:32	+0:08
10-12	0:28	0:09	-0:19	0:11	-0:16
12-14	0:29	0:12	-0:17	0:19	-0:10
14-16	0:42	0:15	-0:26	0:21	-0:21
16-18	0:25	0:34	+0:09	0:57	+0:32
18 ~	0:25	0:07	-0:18	0:11	-0:14
Day Avg.	0:30	0:15	-0:14	0:22	-0:08



Appendix E: Daily Estimated 90th Percentile Wait Time Comparisons (Visual vs. SMATS Cases)

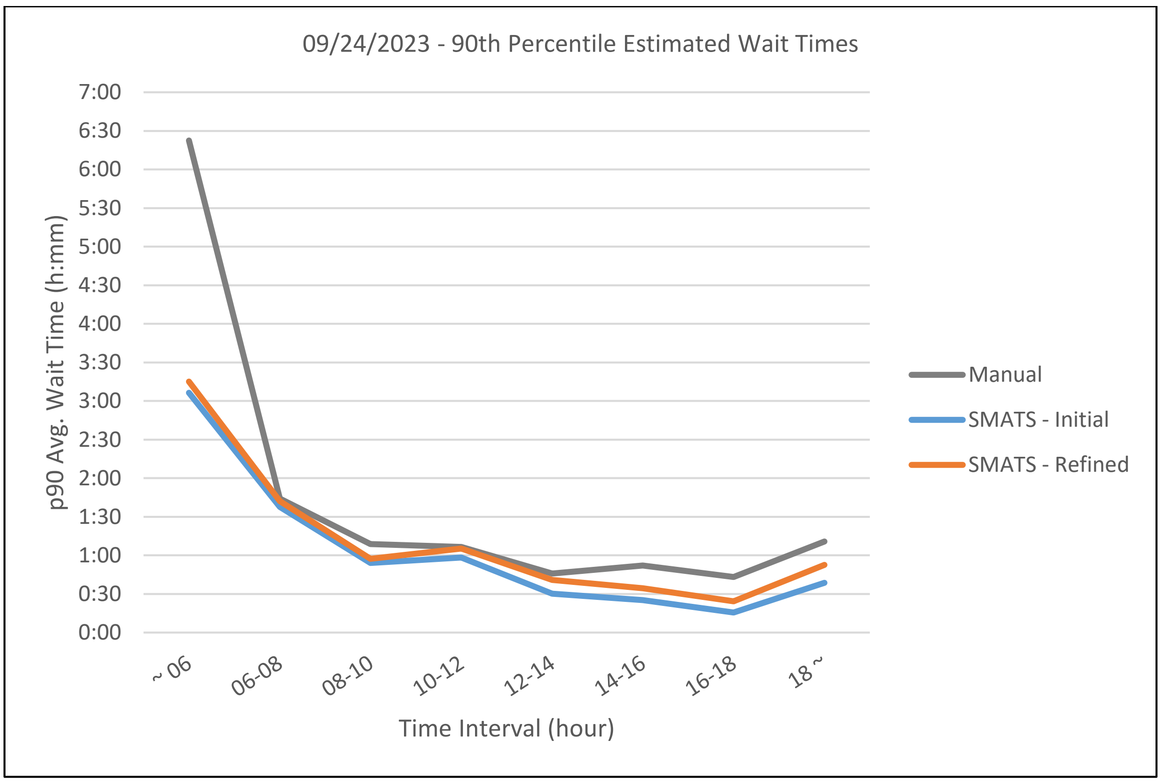
90th Percentile Average Wait Times Comparison for 9/21/2023 Manual vs. SMATS Cases

09/21/2023 - 90th Percentile Estimated Wait Times					
Time Interval	Manual	SMATS - Initial		SMATS - Refined	
	p90 Avg. Wait Time	*p90 Avg. Wait Time*	*Diff. from Manual*	*p90 Avg. Wait Time*	*Diff. from Manual*
~ 06	0:32	0:10	-0:21	0:11	-0:21
06-08	0:59	0:11	-0:48	0:50	-0:08
08-10	1:55	1:39	-0:16	1:41	-0:14
10-12	2:26	2:02	-0:23	2:08	-0:17
12-14	0:59	2:45	+1:45	3:08	+2:08
14-16	0:45	0:06	-0:39	0:18	-0:27
16-18	0:30	0:23	-0:07	0:34	+0:03
18 ~	0:57	0:46	-0:10	1:02	+0:05
Day Avg.	2:10	1:33	-0:36	1:43	-0:26



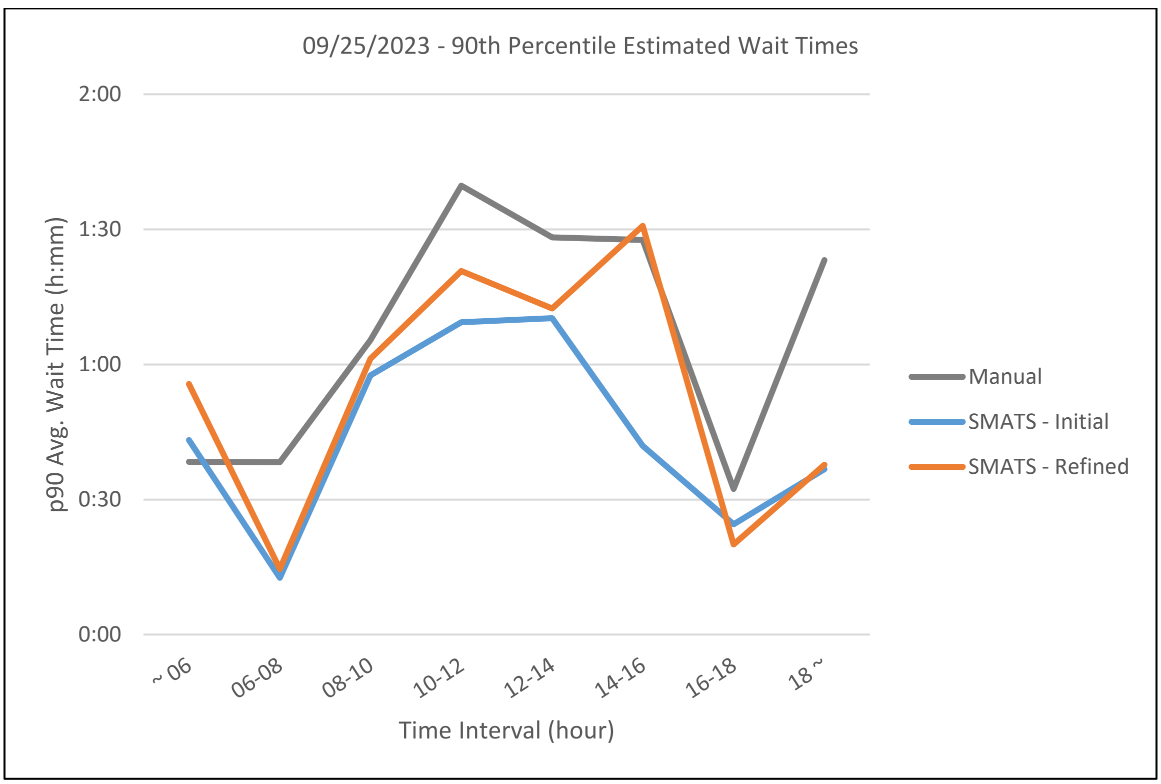
90th Percentile Average Wait Times Comparison for 9/24/2023 Manual vs. SMATS Cases

09/24/2023 - 90th Percentile Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	p90 Avg. Wait Time	*p90 Avg. Wait Time*	*Diff. from Manual*	*p90 Avg. Wait Time*	*Diff. from Manual*
~ 06	6:22	3:06	-3:16	3:15	-3:07
06-08	1:44	1:37	-0:06	1:42	-0:02
08-10	1:08	0:54	-0:14	0:57	-0:11
10-12	1:06	0:58	-0:08	1:05	-0:01
12-14	0:45	0:30	-0:15	0:40	-0:04
14-16	0:52	0:25	-0:26	0:34	-0:17
16-18	0:43	0:15	-0:27	0:24	-0:18
18 ~	1:10	0:38	-0:32	0:52	-0:18
Day Avg.	1:11	0:57	-0:14	1:28	+0:16



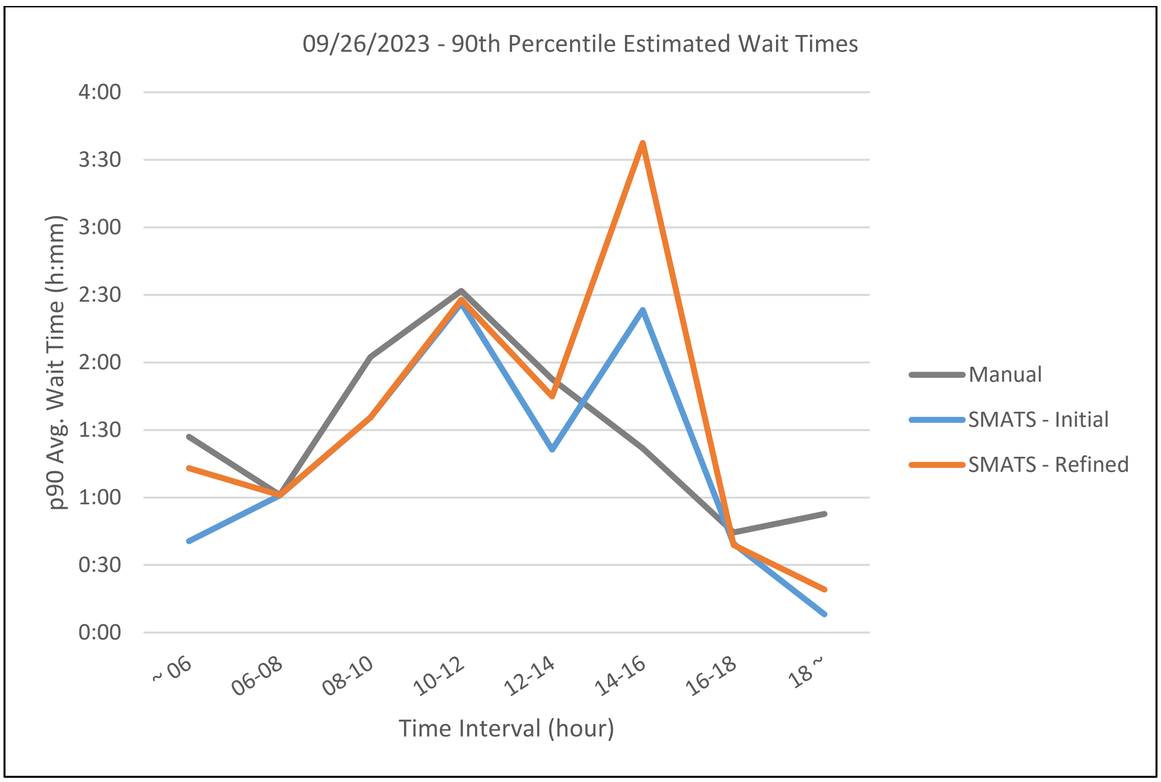
90th Percentile Average Wait Times Comparison for 9/25/2023 Manual vs. SMATS Cases

09/25/2023 - 90th Percentile Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	p90 Avg. Wait Time	*p90 Avg. Wait Time*	*Diff. from Manual*	*p90 Avg. Wait Time*	*Diff. from Manual*
~ 06	0:38	0:43	+0:04	0:55	+0:17
06-08	0:38	0:12	-0:25	0:14	-0:23
08-10	1:05	0:57	-0:07	1:01	-0:04
10-12	1:39	1:09	-0:30	1:20	-0:18
12-14	1:28	1:10	-0:17	1:12	-0:15
14-16	1:27	0:41	-0:45	1:30	+0:03
16-18	0:32	0:24	-0:07	0:19	-0:12
18 ~	1:23	0:36	-0:46	0:37	-0:45
Day Avg.	1:30	0:53	-0:36	1:09	-0:20



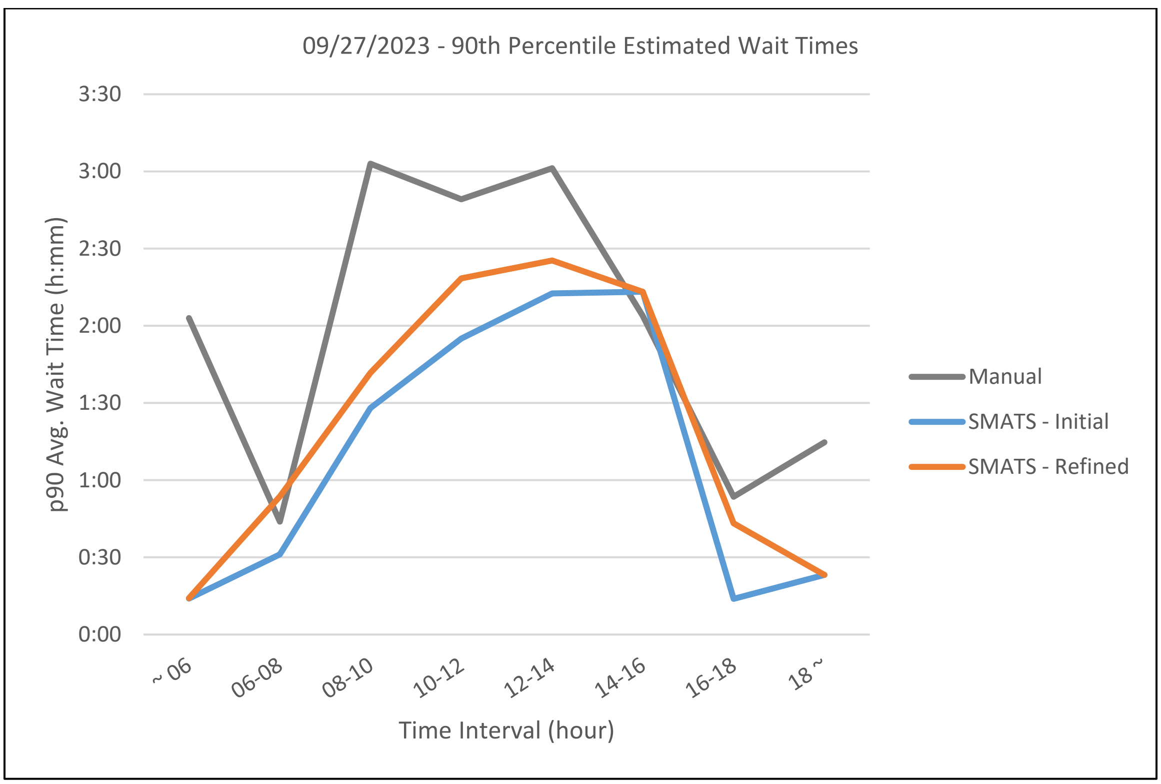
90th Percentile Average Wait Times Comparison for 9/26/2023 Manual vs. SMATS Cases

09/26/2023 - 90th Percentile Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	p90 Avg. Wait Time	*p90 Avg. Wait Time*	*Diff. from Manual*	*p90 Avg. Wait Time*	*Diff. from Manual*
~ 06	1:26	0:40	-0:46	1:12	-0:13
06-08	1:01	1:00	-0:00	1:01	+0:00
08-10	2:02	1:35	-0:26	1:35	-0:26
10-12	2:31	2:26	-0:05	2:27	-0:03
12-14	1:52	1:21	-0:31	1:44	-0:07
14-16	1:21	2:23	+1:01	3:37	+2:15
16-18	0:44	0:39	-0:05	0:38	-0:05
18 ~	0:52	0:08	-0:44	0:19	-0:33
Day Avg.	2:11	1:39	-0:31	2:01	-0:09



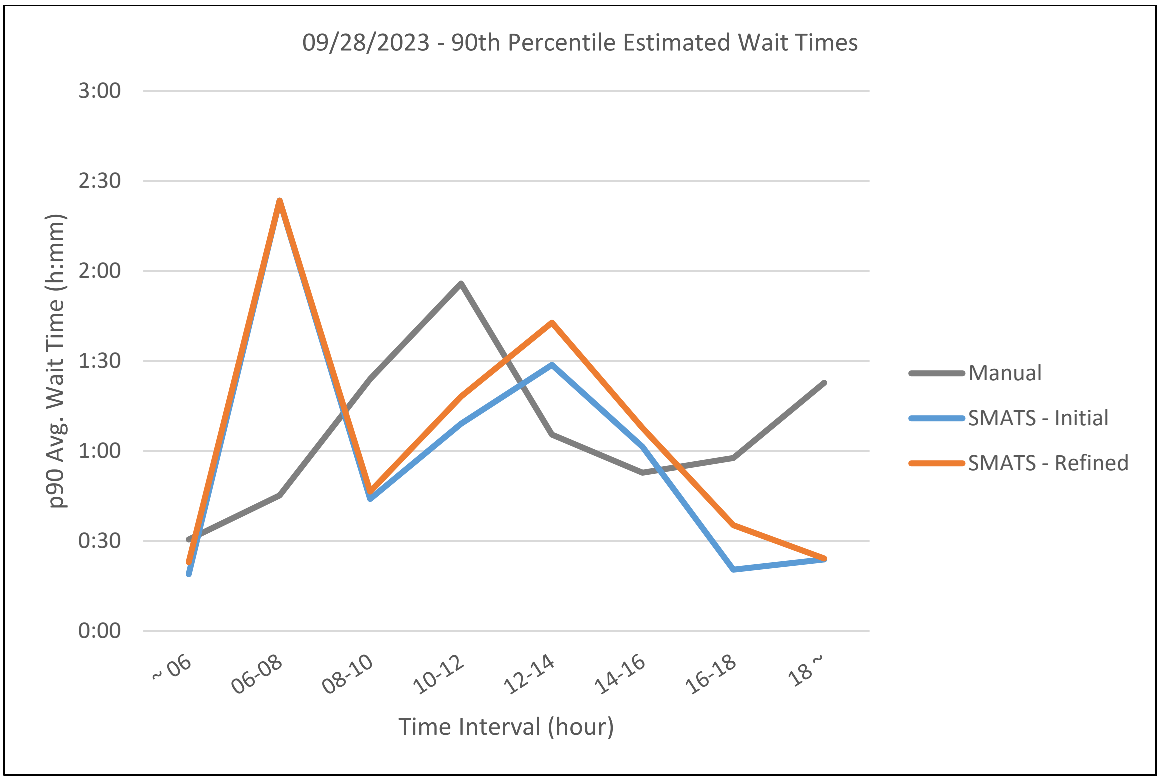
90^{th} Percentile Average Wait Times Comparison for 9/27/2023 Manual vs. SMATS Cases

09/27/2023 - 90th Percentile Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	p90 Avg. Wait Time	*p90 Avg. Wait Time*	*Diff. from Manual*	*p90 Avg. Wait Time*	*Diff. from Manual*
~ 06	2:03	0:13	-1:49	0:14	-1:48
06-08	0:43	0:31	-0:12	0:53	+0:09
08-10	3:03	1:28	-1:34	1:41	-1:21
10-12	2:49	1:55	-0:54	2:18	-0:30
12-14	3:01	2:12	-0:48	2:25	-0:35
14-16	2:03	2:13	+0:09	2:13	+0:09
16-18	0:53	0:13	-0:39	0:43	-0:10
18 ~	1:14	0:23	-0:51	0:23	-0:51
Day Avg.	2:50	1:41	-1:08	1:58	-0:52



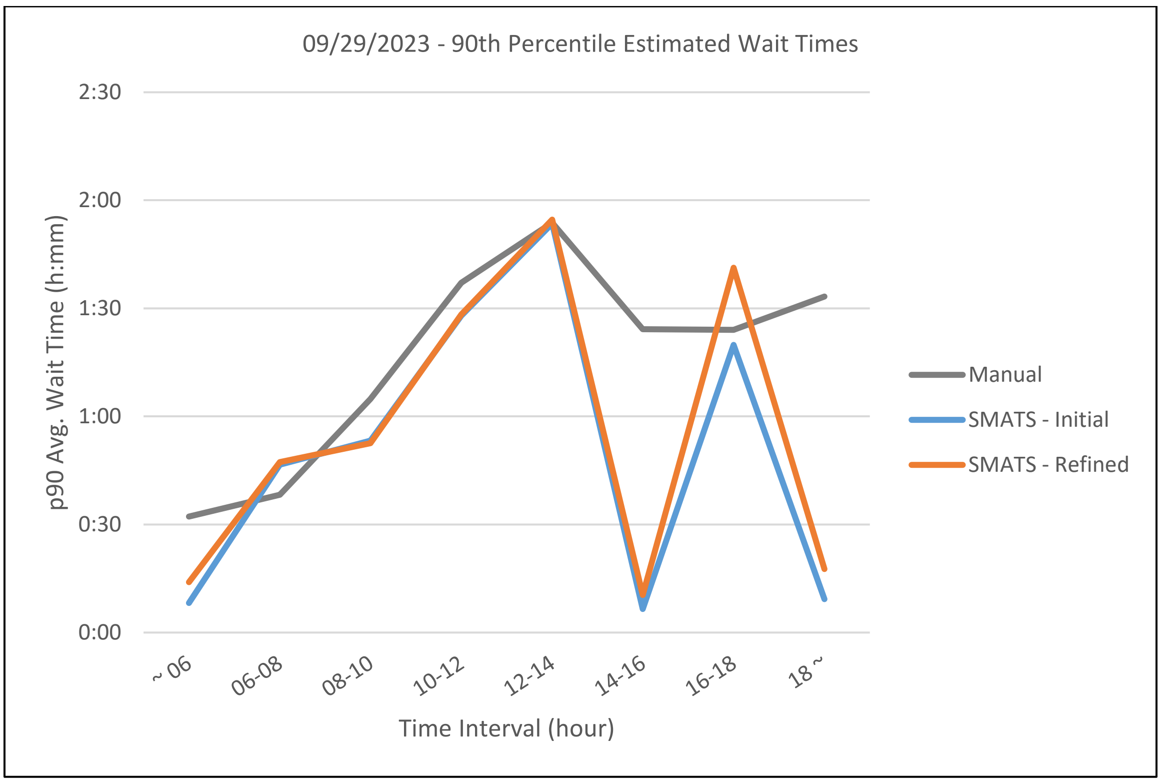
90th Percentile Average Wait Times Comparison for 9/28/2023 Manual vs. SMATS Cases

09/28/2023 - 90th Percentile Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	p90 Avg. Wait Time	*p90 Avg. Wait Time*	*Diff. from Manual*	*p90 Avg. Wait Time*	*Diff. from Manual*
~ 06	-	0:18	-	0:22	-
06-08	0:30	2:23	+1:52	2:23	+1:52
08-10	0:45	0:43	-0:01	0:46	+0:01
10-12	1:23	1:09	-0:14	1:18	-0:05
12-14	1:55	1:28	-0:27	1:42	-0:13
14-16	1:05	1:01	-0:04	1:07	+0:02
16-18	0:52	0:20	-0:32	0:35	-0:17
18 ~	0:57	0:23	-0:33	0:24	-0:33
Day Avg.	1:22	0:58	-0:24	1:18	-0:04



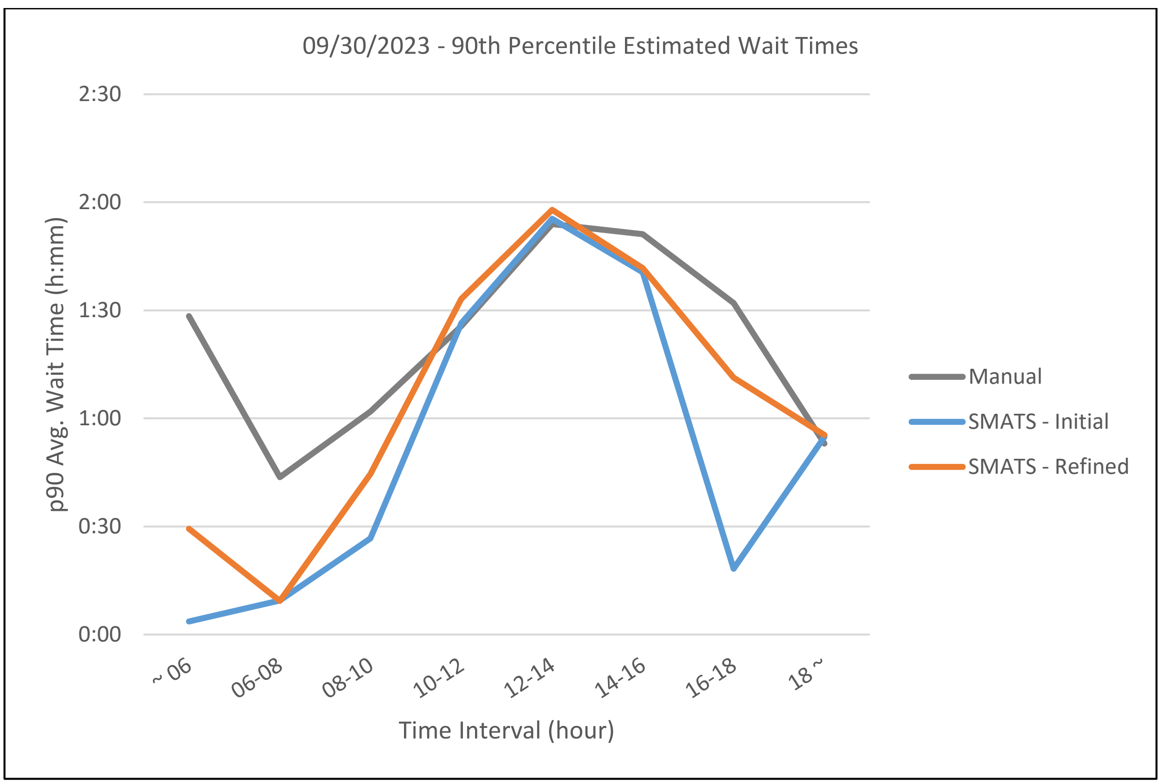
90th Percentile Average Wait Times Comparison for 9/29/2023 Manual vs. SMATS Cases

09/29/2023 - 90th Percentile Estimated Wait Times					
	Manual	**SMATS - Initial**		**SMATS - Refined**	
Time Interval	*p90 Avg. Wait Time*	*p90 Avg. Wait Time*	*Diff. from Manual*	*p90 Avg. Wait Time*	*Diff. from Manual*
~ 06	0:32	0:08	-0:24	0:13	-0:18
06-08	0:38	0:46	+0:08	0:47	+0:09
08-10	1:04	0:53	-0:11	0:52	-0:12
10-12	1:37	1:28	-0:09	1:28	-0:08
12-14	1:53	1:53	-0:00	1:54	+0:00
14-16	1:24	0:06	-1:17	0:10	-1:13
16-18	1:24	1:19	-0:04	1:41	+0:17
18 ~	1:33	0:09	-1:23	0:17	-1:15
Day Avg.	1:34	1:12	-0:21	1:27	-0:06



90th Percentile Average Wait Times Comparison for 9/30/2023 Manual vs. SMATS Cases

09/30/2023 - 90th Percentile Estimated Wait Times					
	Manual	**SMATS - Initial**		**SMATS - Refined**	
Time Interval	*p90 Avg. Wait Time*	*p90 Avg. Wait Time*	*Diff. from Manual*	*p90 Avg. Wait Time*	*Diff. from Manual*
~ 06	1:28	0:03	-1:24	0:29	-0:59
06-08	0:43	0:09	-0:34	0:09	-0:34
08-10	1:01	0:26	-0:35	0:44	-0:17
10-12	1:25	1:26	+0:00	1:33	+0:07
12-14	1:53	1:55	+0:01	1:57	+0:03
14-16	1:51	1:40	-0:10	1:41	-0:09
16-18	1:32	0:18	-1:13	1:11	-0:20
18 ~	0:53	0:54	+0:01	0:55	+0:02
Day Avg.	1:39	1:25	-0:13	1:38	-0:00



90th Percentile Average Wait Times Comparison for 10/01/2023 Manual vs. SMATS Cases

10/01/2023 - 90th Percentile Estimated Wait Times					
Time Interval	**Manual**	**SMATS - Initial**		**SMATS - Refined**	
	p90 Avg. Wait Time	*p90 Avg. Wait Time*	*Diff. from Manual*	*p90 Avg. Wait Time*	*Diff. from Manual*
~ 06	0:50	-	-	-	-
06-08	0:40	0:08	-0:32	0:08	-0:32
08-10	0:42	0:35	-0:07	0:37	-0:05
10-12	0:53	0:17	-0:35	0:21	-0:31
12-14	0:55	0:20	-0:35	0:42	-0:13
14-16	1:10	0:41	-0:29	0:41	-0:29
16-18	0:53	2:47	+1:54	4:28	+3:35
18 ~	0:53	0:14	-0:38	0:15	-0:38
Day Avg.	0:56	0:30	-0:25	0:37	-0:18