ESTIMATING TRANSIT RIDERSHIP PATTERNS THROUGH AUTOMATED DATA COLLECTION TECHNOLOGY: A CASE STUDY IN SAN LUIS OBISPO, CALIFORNIA

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ABSTRACT

Estimating Transit Ridership Patterns Through Automated Data Collection Technology::
A Case Study in San Luis Obispo, California

Ashley Jiyoung Kim

Public transportation offers a crucial solution to the travel demand in light of national and global economic, energy, and environmental challenges. If implemented effectively, public transit offers an affordable, convenient, and sustainable transportation mode. Implementation of new technologies for information-harvesting may lead to more effective transit operations. This study examines the potential of automated data collection technologies to analyzing and understand the origin-destination flow patterns, which is essential for transit route planning and stop location placement.

This thesis investigates the collection and analysis of data of passengers onboard San Luis Obispo Transit buses in February and March 2017 using Bluetooth (BT) and automatic passenger counter (APC) data. Five BlueMAC detectors were placed on SLO Transit buses to collect Bluetooth data. APC data was obtained from San Luis Obispo Transit. The datasets were used to establish a data processing method to exclude invalid detections, to identify and process origin and destination trips of passengers, and to make conclusions regarding passenger behavior. The filtering methods were applied to the Bluetooth data to extract counts of unique passenger information and to compare the filtered data to the ground-truth APC data. The datasets were also used to study the San Luis Obispo Downtown Farmer's Market and its impact on transit ridership demand. The investigation revealed that after carefully employing the filters on BT data there were no consistent patterns in differences between unique passenger counts obtained from APC data and the BT data. As a result, one should be careful in employing BT data for transit OD estimation. Not every passenger enables Bluetooth or owns a Bluetooth device, so relying on the possession of Bluetooth-enabled devices may not lead to a random sample, resulting in misleading travel patterns. Based on the APC data, it was revealed that transit ridership is 40% higher during the days during which Higuera Street in Downtown San Luis Obispo is used for Farmer's Market – a classic example of tactical urbanism. Increase in transit ridership is one of the aspects of tactical urbanism that may be further emphasized. With rapidly-evolving data collection technologies, transit data collection methods could expand beyond the traditional onboard survey. The lessons learned from this study could be expanded to provide a robust and detailed data source for transit operations and planning.

Keywords: Bluetooth, transit reliability, origin destination, mobility, transit planning, transit, passenger sensing, origin destination matrix, public transport, bus, data collection, data filtering, automatic passenger counter

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LIST OF ACRONYMS

APC	Automated Passenger Counter
AFC	Automated Fare Collection
AFH	Adaptive Frequency Hopping
BART	Bay Area Rapid Transit
BT	Bluetooth
dBi	Decibel over Isotropic
dBm	Decibel (references to milliwatts)
FHS	Frequency Hopping Synchronization
GHz	Gigahertz
GIS	Geographic Information System
GPS	Global Positioning System
ID	Identifier
ITS	Intelligent Transportation Systems
kW	Kilowatt
MAC	Media Access Control
MPH	Miles per Hour
mW	Milliwatt
OD	Origin-Destination
OUI	Organizationally Unique Identifier
PAN	Personal Area Network
PII	Personally Identifiable Information
RTA	Regional Transit Authority
SLO	San Luis Obispo

1. INTRODUCTION

Public transportation offers a crucial solution to the origin-destination (OD) travel demand and the nation's economic, energy, and environmental challenges. If implemented effectively, public transit offers an affordable, convenient, and sustainable transportation mode. Individuals, families, communities, and businesses benefit from public transportation by providing personal mobility, access to jobs, and the freedom to get to work, school, social events, or doctor's appointments.

There are high public expectations for the services that public transportation systems provide. It is essential for public transit agencies to provide reliable service needed to attract choice riders, generate a greater financial and trustworthy return, and maintain success for the future. It is essential to implement new technologies for information-harvesting and effective real-time operations.

Analyzing and understanding the origin-destination flow patterns of passengers is essential for transit route planning and stop location placement. Using the traditional methods of on-board surveys to estimate origin-destination flows is labor intensive and time-consuming. Some transit agencies use data from smart card transactions to determine the origin and destination of trips. With origin-destination flows detected by Bluetooth devices, travel patterns could be identified and analyzed to provide conclusions and recommendations for future transit planning, operational analysis, and service management.

1.1 Research Objectives

This thesis is a case study evaluation of the reliability of data collected with emerging or smart transit technologies, such as Bluetooth and Automatic Passenger Counters (APC). The study conducts technology-based counts on SLO Transit to compare Bluetooth data with APC data, and to establish a reliable data processing method to exclude invalid detections. The following questions are addressed:

- What kind of passenger behavior information can be obtained from emerging technology data collection to use in transit service planning?
- How can this information be used for decision-making within transit agencies?

By answering these questions, readily obtainable data can contribute to planning by transit agencies.

1.2 Overview

In this thesis, the literature review, research design, results, and conclusions are located in their respective chapters. Chapter 2, the literature review, covers literature on previous research relevant to origin-destination data collection and utilization of Bluetooth technology in transportation engineering. The background and technical specifications of Bluetooth are explained for the reader to understand its applications in transportation. Chapter 3 outlines the research design. Chapter 4 describes the data analysis procedure and results of the study. Chapter 5 contains the summary of conclusions along with recommendations for future research.

2. LITERATURE REVIEW

2.1 Methods of Origin-Destination Data Collection

This chapter reviews previous data collection techniques for origin-destination trips to create origin-destination matrices for public transportation networks.

2.1.1 Automated Passenger Counter Data

Automated passenger counter technology (APC) is adopted for bus services. APC systems provide passenger boarding and alighting counts. APC technology allows data collection efforts at a reasonable cost. The devices count passengers entering and exiting the transit vehicle, eliminating the need for ride checkers employed by transit agencies to count passengers on board. The devices also further eliminate the manual error from counting passengers. Different methods of APCs include: treadle mats, infrared beams, passive thermal, digital cameras, ultrasound, and light beams. Treadle mats count when they sense the pressure of passengers traversing the bus steps. Infrared beams, passive thermal detectors, and ultrasound detect the presence of the passenger and count them. Digital cameras record passenger movement, but the disadvantage derives from inaccuracies from image capture. Shadows, overlapping objects, and lighting could impact the data analysis (APTS, 2011).

The passenger boarding and alighting counts are not linked, but could provide information regarding the origin-destination flows. The boarding count at a bus stop on a bus trip is the sum of passenger flows originating from that bus stop on that bus trip. Boarding and alighting counts provide indirect information on estimating origin-destination patterns. The error associated with APCs is likely systematic and random –

instances including: mechanical problems, environmental factors, passenger behavior, and data processing. (Mishalani, 2011).

2.1.2 Automated Fare Collection System

Another method of origin-destination collection includes the automated fare collection (AFC) systems which provide an efficient and cost-saving alternative to traditional manual fare collection methods. AFC data could be used to generate origin-destination matrices for performance measurement and service planning. Errors arise due to the limitation that most AFC systems record passenger boarding location at the bus-route level, making it difficult to obtain the data on the specific bus stops where passengers board.

In New York City, its transit system utilizes an automated fare collection system known as MetroCard. Its fare boxes record the serial number of the MetroCard and the time and location (subway turnstile or bus number) with each scan. To determine the sequence of daily trips on each MetroCard, the MetroCard serial numbers were sorted, then the sequence of the trips and stations used by MetroCard was extracted. Then, algorithms were applied to infer a destination station for each origin. Using the AFC eliminates the need for system-wide origin-destination surveys, requires no onboard passenger surveying, and eliminates response bias (such as low response rates from certain demographic groups). Since MetroCard data is available 365 days a year, origin-destination estimation could be repeated to account for seasons and to improve accuracy (Barry et al., 2002). Disadvantages of the AFC system include the incapability of completely tracking passenger movements throughout the transit system such as arriving

at the station or transferring at a bus stop. Further disadvantages include high energy consumption, high initial investment, and privacy concerns (Yuval, 2016).

An early example of AFC derives from the Bay Area Rapid Transit (BART) system. OD matrices were created using fare card data in the BART system. The fare system on BART is based on distance travelled, which requires passengers to scan their fare cards on entry and exit from the system. The entry and exit data provided a more accurate passenger trip OD matrix compared to entry-only systems (Buneman, 1984).

In Seoul, Korea, smart card data was used to study public transit use. One feature that distinguishes the Seoul smart card from many transit agencies is that it records trip entry and exit times, locations, the trip chains with interchanges. The smart card data is used as a basis for describing the characteristics of public transit use: number of transfers, boarding time, hourly trip distribution of number of trips for different transit modes, and travel time distribution for all transit modes and user types. (Park, 2008).

2.1.3 Survey Data

Public transport systems often send employees to conduct passenger counts or onboard surveys of passengers to obtain origin-destination data. The Charlotte Area Transit System (CATS) conducted a system-wide origin-destination study to understand its transit market and to collect data before constructing the LYNX Light Rail Blue Line extension. The team conducted on-to-off surveys, collected data via GPS barcode scanners given to customers as they boarded and collected as they alighted. The team also conducted onboard surveys and in-person interviews using web-enabled tablets (RSG, 2017).

AC Transit conducted a survey of its passengers to collect trip information towards its planning initiatives. The survey included a two-minute onboard survey limited to origin, destination, and contact information. The passengers were followed up by a phone survey to obtain the passenger's trip information. AC Transit used telephone surveys to minimize literacy issues that contribute to non-response bias (Redhill Group, Inc., 2013).

The onboard survey method provides opportunities for transit agencies to interact in person with its passengers and collect information beyond origin-destination demand. Disadvantages of the in person survey method are that it is labor-intensive, time consuming, has privacy concerns, and suffers from non-response bias.

2.2 Bluetooth Functionality & BlueMAC Devices

Invented in 1994 by engineers from Swedish company Ericcson, Bluetooth enables wireless connection to share music, images, and other data over a personal area network (PAN). The PAN is defined by the device's antenna (Vo, 2011). The technical specifications of Bluetooth are described, including frequencies and types and ranges of antennas. A radio frequency involved the rate at which radio signals are transmitted. The signal range of a Bluetooth device is the range in which Bluetooth devices could be discoverable.

2.2.1 Overview of Bluetooth and MAC Addresses

A Bluetooth device uses radio waves to wirelessly connect to a phone or computer. Communication between two devices occurs over short-range networks called piconets. Bluetooth utilizes radio waves over short–range networks known as piconets to send and receive data. Bluetooth technologies provide low-cost, low-power, and secure

wireless communication. Its economic value led to its installation in carry-in and embedded vehicle systems: in-dash navigation systems and entertainment systems, laptops, mobile phones, tablets, speakers, smart watches, and headphones (Bluetooth, 2017). Figure 1 below illustrates an example scenario of detection (Libelium, 2012). The pedestrians and vehicles with mobile devices wirelessly connect to the Bluetooth detector mounted on the light pole. Some pedestrians wirelessly connect to Wi-Fi with their devices. The Bluetooth detector collects the detections, and wirelessly transmits the data through 3G to a database.

Bluetooth operates by proximity. When Bluetooth-enabled devices are within 3 feet to 300 feet of one another, they have the ability to connect and allow seamless transmission of voice and data. Bluetooth devices can connect to multiple devices simultaneously without interfering existing Bluetooth connections (Carpenter, 2012).

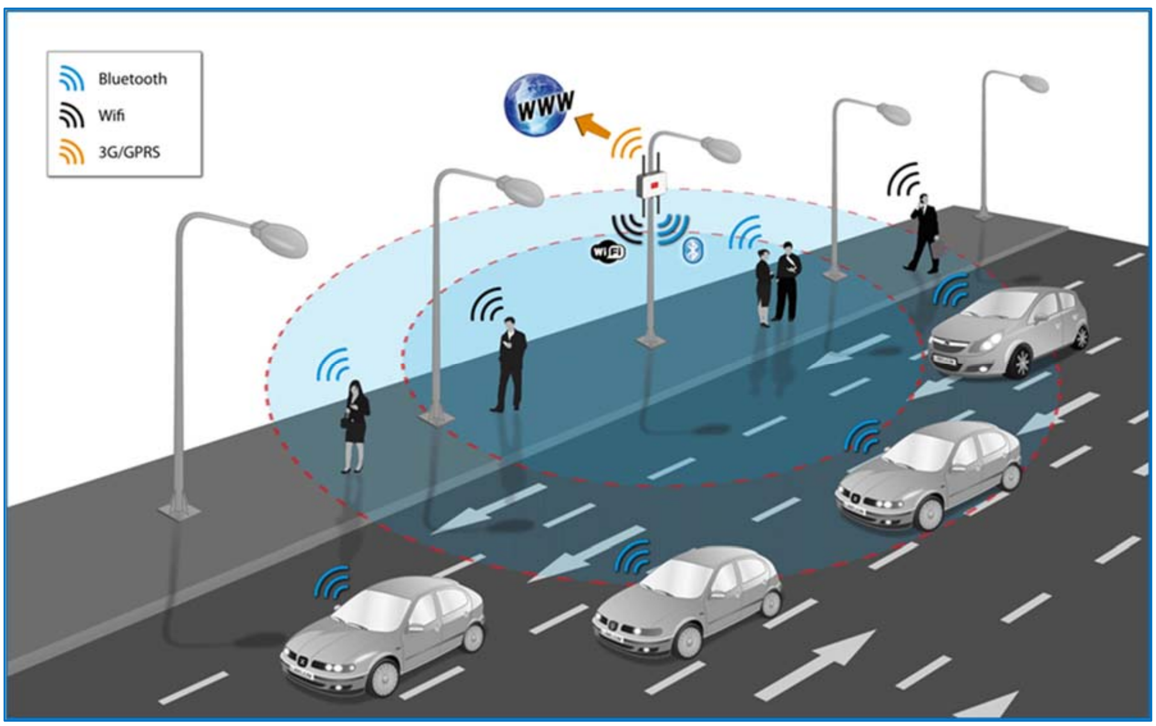


Figure 1: Bluetooth Sensitivity

2.2.2 Bluetooth MAC ID

BlueMAC is a brand of Bluetooth data collection technology, which develops devices that match media access control (MAC) addresses between devices. Each device emits a unique 48-bit MAC identifier (ID). The ID expressed as a sequence of twelve hexadecimal digits (six groups of two digits separated by a colon, for example: 00:22:CE:28:18:81). Each MAC ID is specific to each device, but the MAC ID is not linked to a specific person. The MAC ID is generated in two stages: the first half is assigned by the device vendor or manufacturer and is termed the Organizationally Unique Identifier (OUI), and the second half is assigned to a specific device. Therefore, the MAC ID does not contain any personal information and renders privacy concerns a nonissue. Furthermore, most devices now give the user the option to set privacy settings also known as "discovery mode" so their device is not detectable by other Bluetooth devices. The detector uses the MAC address to calculate travel time and speed between match points. Figure 2 shows a diagram depicting the travel time calculation (Libelium, 2012).

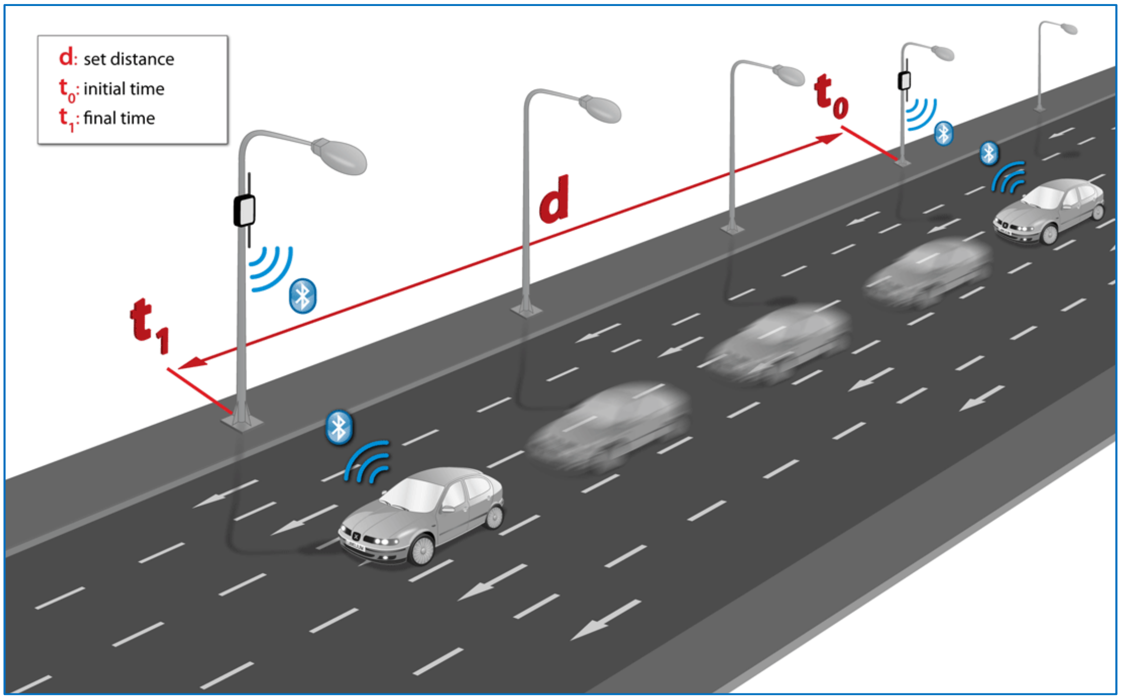


Figure 2: Bluetooth Travel Time Depiction

2.2.3 Antenna and Range

Bluetooth sends radio signals ranging from 3 feet to 330 feet. The frequencies of the radio waves are sent from 2.402 gigahertz (GHz) to 2.48 GHz, internationally concurred for use of scientific, industrial, and medical devices.

Antenna polarization may be directional or omni-directional. Directional sends and receives data from specific angles in one direction. Omni-directional antennae send and receive data from any direction (Abedi, Bhaskar, Chung, & Miska, 2015). The strength of an antenna is measured in decibels isotropic (dBi), and it is determined by the antenna's ability to concentrate radio frequency energy in a specific direction. Omni-directional antennas with gains from 9 to 12 dBi are ideal for road traffic data collection (Porter, Kim, Magana, Poocharoen, & Arriaga, 2013). Larger antennas allow for more gains and data, but disadvantages arise in more anomalies and longer data processing times. Smaller gain antennas have a smaller range, lesser anomalies, and less data

processing time. Smaller gain antennas are ideal for small projects with high pedestrian and bicycle movements (Abedi et al., 2015).

2.2.4 Data Capture and Detection Rate

When two Bluetooth devices communicate, the devices discover each other by inquiry and paging. The inquiry step takes 10.24 seconds. During this time, the Bluetooth devices join 32 channels which is a subset of the 79 channels available for Bluetooth. The 32 channels contain 16 subsets called trains, and a scan of each train takes 0.01 seconds. Bluetooth requires that each scan is repeated 256 times for enough time to collect all inquiry responses from other Bluetooth devices. Bluetooth also requires at least 3 train switches to run, so two iterations of each train occur. 2 trains times 2 iterations times 256 iterations times 0.01 seconds equals 10.24 seconds, the minimum time required for the discovery of all Bluetooth devices within the range (Woodings et al, 2002). When discovered, the Bluetooth technology uses adaptive frequency hopping (AFH) and frequency hopping synchronization (FHS) to connect up to eight different devices at the same time (Franklin & Layton, 2011).

The type of Bluetooth antenna and their placement impacts the detection rates, quantity, and quality of the data. A study on Bluetooth detection found that Bluetooth-enabled mobile phones placed on a vehicle's dashboard has three to five times higher detection rate than Bluetooth-enabled phones in pockets or purses. Slow-moving vehicles were detected more frequently than fast-moving vehicles due to antenna lag (Stevanovic, Olarte, Galletebeitia, Galletebeitia, & Kaisar, 2014).

2.2.5 Radio Classes and Power

Manufacturers can set the range limits to meet the needs of their product's intended users. Class 3 radios include ranges of 3 feet. Class 2 radios, commonly used on mobile phone devices, provide a range of at least 33 feet. Class 1 radios offer a minimum range of 330 feet, and are typically used for industrial applications.

Bluetooth technology was designed to operate on low power. Class 1 radios operate at a maximum of 100 mW or 20 dBm, Class 2 radios operate at 2.5 mW or 4 dBm, and Class 3 radios operate at a rate of 1mW or 0 dBm. For comparison, a simple laser pointer used in presentations produces 5mW of light power. A typical hearing aid consumes less than 1mW. Furthermore, 1000 mW, or 1 kW, could power a small electric heater (Vo, 2011).

2.2.6 Known Sources of Error

Previous research has shown that some individuals carry multiple Bluetooth-enabled devices, creating a source of error when estimating passenger origins and destinations. Furthermore, the Bluetooth-detected devices represent a select sample of the ridership population who carry mobile devices, and this select sample may have different travel patterns than those of the overall population. Therefore, this study assumes that each passenger carries only one mobile device (Dunlap, 2016).

Sources of error depend on the installation, implementation, and facility used in the study. The signal path is influenced by physical obstacles. Bluetooth signals could travel through glass, but may reflect on surfaces to establish a wireless connection. Errors could occur from a malfunction with the devices for unknown reasons and low battery power which results in no data collection (Purser, 2016).

Another source of error derives from cloned MAC IDs. This is not a normal practice, but some Bluetooth devices carried by taxi fleet have devices that are cloned per the fleet operator requirements. The cloned IDs leads to ambiguous results in Bluetooth MAC ID matching. However, the percentage of cloned MAC IDs is negligible compared to massive data collection captured by Bluetooth detectors (Bhaskar et. Al, 2014).

MAC detectors reported travel times not significantly different with 95% confidence from Global Positioning System (GPS) devices 83% of the time (Stevanovic et al., 2014).

2.2.7 Comparison to Other Methods

In the past, mobile phone tracking has been used to measure flows of passengers on intercity trips. However, the results have low spatial resolution and are more suited for long distance trips such as highways. Due to Bluetooth's popularity and widespread usage, it is a useful source for capturing individual trips. Figure 3 below shows the comparison of passenger trip detection using Bluetooth versus electronic ticketing and surveys (Kostakos, 2013).

	Method of OD estimation		
	Bluetooth detection	**Electronic ticketing**	**Survey**
Sample size	~10%	>50%	~3%
Spatial accuracy of destination data	High	Relies on inferencing (which introduces bias)	High (explicitly stated by respondent)
Representativeness and sample bias	Demographic bias on technology adoption	Bias if all passengers do not swipe ticket	Bias due to sampling technique, human memory, and self-selection of respondents
Passenger effort	Enable Bluetooth	Swipe ticket	Answer questionnaire

Figure 3: Bluetooth versus Electronic Ticketing and Surveys

Regarding vehicle travel times, “ground truth” data has been collected using test vehicle or “floating car” methods. Bluetooth reads have captured data consistently with the ground truth (Koprowski, 2012). Bluetooth sensors were also consistent with ground truth and with TRANSMIT data. TRANSMIT data captures collection tags and fixed sensors. Furthermore, at multiple areas, Bluetooth outperformed INRIX data sets (Liu, Chien, & Kim, 2012).

2.2.8 Privacy Concerns

The highest concern regarding any traffic data collection procedure is privacy. GPS and cellular phone tracking for travel data collection purposes contain personally identifiable information (PII). However, MAC addresses do not contain any personal information, but provide the unique codes that allow for accurate travel time and origin-destination calculations.

2.3 Transportation Engineering Application of Bluetooth Data Collection

2.3.1 Multimodal Considerations

Beyond vehicle travel times and patterns, Bluetooth data collection can help improve transit, bicycle, and pedestrian facilities. By detecting commute patterns, Bluetooth data can present potential ridership for a new transit service, thereby attracting more ridership (Kieu, Bhaskar, & Chung, 2012). By attracting more transit riders, public transportation can be further studied to decrease congestion and emissions (Weinzerl and Hagemann, 2007). The National Cooperative Highway Research Program Report 797 notes that pedestrians and cyclists tend to make shorter trips, making it more difficult to detect (Ryus et al., 2014).

2.3.2 Intelligent Transportation Systems Evaluations

Bluetooth travel patterns can provide better bicycle, pedestrian, transit, and vehicle movements through intelligent transportation systems (ITS) than traditional data sources. Reliable bus travel time data could help improve corridor signals by providing information for bus preemption and prioritization signal design. Signal timing could be calculated to anticipate heavier vehicular flows based on travel time (Kieu et al., 2012). Conducting before and after studies of a changed bus route or upgraded signal determines effectiveness and areas of improvement (Quayle & Koonce, 2010). Collecting data on pedestrian and bicycle movements have provided information on projected demand on similar projects (Ryus et al., 2014).

2.3.3 Mass Movements

Bluetooth travel patterns have been studied for evacuation procedures, work zone effects, and tourism patterns. The data can be used to recognize pedestrian bottlenecks and movements, and in return provide signage to diffuse and guide the crowds. Work zone patterns could be analyzed and applied toward increasing safety and decreasing hazards for construction workers. Portable Bluetooth detection devices were implemented during repaving of I-65 in northwestern Indiana in 2009. Using the data, travel times were displayed in real-time on dynamic message boards (Haseman et al., 2010). Studying movements in these kind of conditions could improve safety conditions and efficiency (Abedi, 2015).

2.3.4 Movements through Airport Security

Bluetooth trackers were deployed at Indianapolis International Airport to measure time for passengers to move from the pre-security, clear the security screening

checkpoint, and enter the walkway on the sterile side. The data collection process provided a more robust data set of screening times than the traditional system of manually distributing timestamped cards to passengers, then collecting them after passing through security. Since the final data collection point was located in the post-security area, the time taken to repackage belongings and put on shoes was also captured. The data from the study suggested the feasibility of using Bluetooth data collection to provide quantitative data for airport managers to make decisions in airport planning (Bullock, 2010). Similarly, travel times and origin-destination patterns could be captured with Bluetooth detectors on transit buses.

2.3.5 Data Processing Best Practices

Due to the significant amount of noise and inconsistences, extraneous data is collected. Data cleaning and processing is necessary prior to conduct the data analysis. For example, when a bus stops, Bluetooth signals from passengers outside the bus or non-passengers near the bus may be detected. Furthermore, some people may turn their device on or off during the trip. Considering these cases, challenges arise when inferring the boarding or alighting stops the passengers use. Prior studies have processed data with the objective of retaining the detection of onboard devices while eliminating the extra device detections. The data was sorted by MAC ID. Then, individual rides were established based on time stamps Δt between consecutive detections from the same device. Travel times greater than the route travel time were assumed part of a different route, correcting for the long rides caused by passengers likely making multiple trips during the data collection period. Data was cleaned through a three filter criteria. The first filter eliminates infrequently detected devices:

$$Detections\ per\ ride > Nthreshold$$

The value of $N_{threshold}$ was assumed 1 detection per ride as moderately conservative but not restrictive to eliminate viable observations. Filter two eliminates rides with unreasonable short and long durations. Trip duration (duration*i*) was calculated as the difference between the initial time detected ($timei_i$) and the final time detected ($timef_i$) for a given ride *i*.

$$Duration_i = timef_i - timei_i$$

Based on historical bus operation records, the running time between any two bus stops in a route is considered. Thus, a ride is considered viable when its duration adheres to the time constraints:

$$LL < duration < UL$$

The final filter deletes detections based on spatial proximity to the nearest bus stop. A given ride was retained only if it was located within a set distance from a transit stop location. For Bluetooth detections, a threshold value of 600 feet was used to retain larger viable sample sizes (Dunlap et al., 2016).

2.4 Tactical Urbanism

Tactical urbanism is an umbrella term used to describe low-cost, temporary changes to the built environment, intending to improve local neighborhoods and city gathering places (Wikipedia, 2016). Case studies across North America reveal the incremental approach to the process of city-building, characterized by community-focus and realistic goals.

2.4.1 Pavement to Plazas

Popularized in New York City, the Pavement to Plaza programs intend to reclaim underutilized asphalt as public space without large capital expenditure. The first program started in 2006 in New York City. The city turned underperforming or unnecessary roadway into pedestrian right of way, providing more public spaces to more people (McLaren, 2015).

Figure 4: Pearl Street Plaza in Brooklyn Before and After Redevelopment

2.4.2 Park(ing) Day

PARK(ing) day is an event where on-street parking spaces are temporarily converted into park-like public spaces. This event is intended to increase the vitality of street life and to draw attention to the amount of space devoted toward the storage of private vehicles. In 2011, 975 on-street parking spaces were temporarily reclaimed in 165 cities, 35 countries, and across six continents (Lydon, 2012).

Figure 5: Park(ing) Day in Nashville, Tennessee

2.4.3 Downtown San Luis Obispo Farmer's Market

Beginning in 1983, the Downtown San Luis Obispo Farmer's Market began. On Thursday nights from 6 to 9 PM, restaurants offer food and barbeque and farmers sell produce. They set up booths along Higuera Street, which is barricaded from vehicular traffic for six blocks.

Analyzing the SLO Transit ridership patterns during the Farmer's Market is crucial. During Farmer's Market times, traffic volumes increase and the downtown parking structures and street parking spaces reach maximum capacity. Furthermore, SLO Transit ridership increases from Cal Poly students traveling from Cal Poly to Downtown. In this study, the APC bus data for SLO Transit routes serving Downtown San Luis Obispo during the Farmer's Market time was analyzed.

2.5 Summary of Literature Review

The low cost for Bluetooth makes it a feasible, potential option for collecting vast data sets. The reasonable cost for APC also allows for data collection efforts in providing passenger boarding and alighting counts. Considering the known sources of error, these data sets can present conclusions on transit patterns. The origin and destination passenger trips can be captured by installing detectors onboard buses. This literature review provides preliminary information toward the research design and methodology and guides the explanations in the results and conclusions.

3. RESEARCH DESIGN

3.1 Study Area

This chapter provides insight into the study area and data collection. The following figures and sections describe the overview, existing conditions, and current SLO Transit routes.

3.1.1 Existing Demographics of the City of San Luis Obispo

The study area includes the City of San Luis Obispo. The City is the county seat of San Luis Obispo County, which is located on the Central Coast of California approximately equidistant from Los Angeles and San Francisco. The California Polytechnic State University is located in San Luis Obispo and is a major source of trip generation, employment, and economic activity.

Per the 2009-2013 US Census, the population of the San Luis Obispo area is estimated at 58,684, including the Cal Poly student population. 99 percent of the population lives within 0.25 mile of a public transit route. The existing demographics are shown in Table 1 below.

Table 1: Existing Demographics of the City of San Luis Obispo

Category	Number of Persons	Percent of Population
Living in Household Without Vehicle	231	1.3%
Youth (under 18 years old)	2,838	5.0%
Elderly (over 60 years old)	3,068	15.0%
Below federal poverty level	14,579	24.8%
Mobility disability	2,259	4.0%

Between 2015 and 2020, the total population is forecast to grow by 1,301. Population is forecasted to increase by 2.3 percent by 2021 (Final Report: SLO County Population, Housing, and Employment Forecast)

3.1.2 Overview of SLO Transit

SLO Transit provides public bus services to the City and the Cal Poly campus through seven fixed routes on weekdays, six routes on Saturdays, and four on Sundays. Service levels decrease when Cal Poly is not in session. The routes provide mobility service to the city and Cal Poly. Six routes meet at the Downtown Transit Center where direct transfers to the Regional Transit Authority (RTA) service can occur.

For the fiscal year 2013 to 2014, average ridership totaled 2,615 passenger boardings on weekdays, 1,197 on Saturdays, and 982 on Sundays. Over the year, ridership totaled 1,029,000 passenger boardings. The busiest routes are Route 4 and 5 which serve almost half of the passengers system-wide.

SLO Transit operates 361,761 vehicle-miles over 29,731 vehicle hours in the year. SLO Transit serves 34.59 passengers for every revenue-hour of service and 2.84 passengers per mile. A maximum of 10 SLO Transit vehicles are on the roads at peak hours on weekdays, 8 on Saturdays, and 7 on Sundays.

3.1.3 Current SLO Transit Routes

The current SLO Transit routes are the following:

Route 1 (Broad/Johnson/University Square): a one-way loop in the southeastern section of San Luis Obispo and a two-way service ending in a loop in the northwestern part of the city to serve the downtown area, as shown in Figure 6.

Route 2 (South Higuera/Suburban): a two-way service serving the southwest area of downtown San Luis Obispo with a two-way service ending in a loop in the downtown area, as shown in Figure 7.

Route 3 (Johnson/Broad/Marigold): a one-way loop through downtown that serves southeastern San Luis Obispo, as shown in Figure 8.

Route 4 (Madonna/Laguna Lake/Cal Poly): a single one-way loop that covers the northwest, north, south, and southwest areas of San Luis Obispo. The route connects Cal Poly to downtown San Luis Obispo, as shown in Figure 9.

Route 5 (Cal Poly/Laguna Lake/Madonna): a single-one-way loop that covers the northwest, north, south, and southwest areas of San Luis Obispo in reverse direction to Route 4. The route connects Cal Poly to downtown San Luis Obispo, as shown in Figure 10.

Route 6A (Cal Poly/Highland): a service connecting Cal Poly to the surrounding area to the west of the campus. Route 6A interlines with Route 6B in figure eight during evenings, weekends, and the summer, as shown in Figure 11.

Route 6B (Cal Poly/Downtown): a service connecting Cal Poly to downtown San Luis Obispo, as shown in Figure 12.

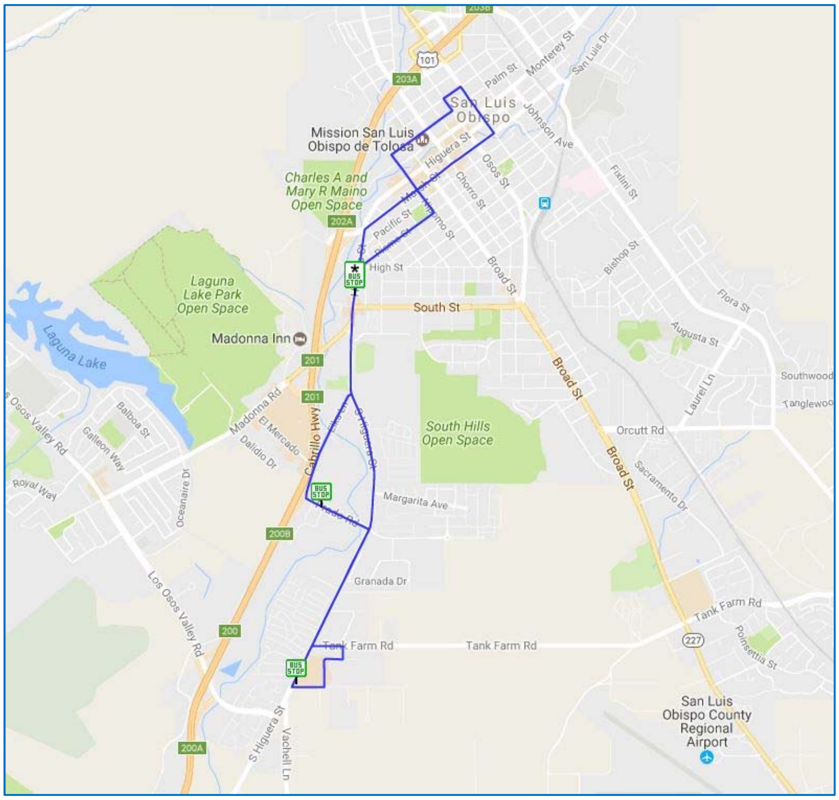


Figure 6: San Luis Obispo Transit Route 1

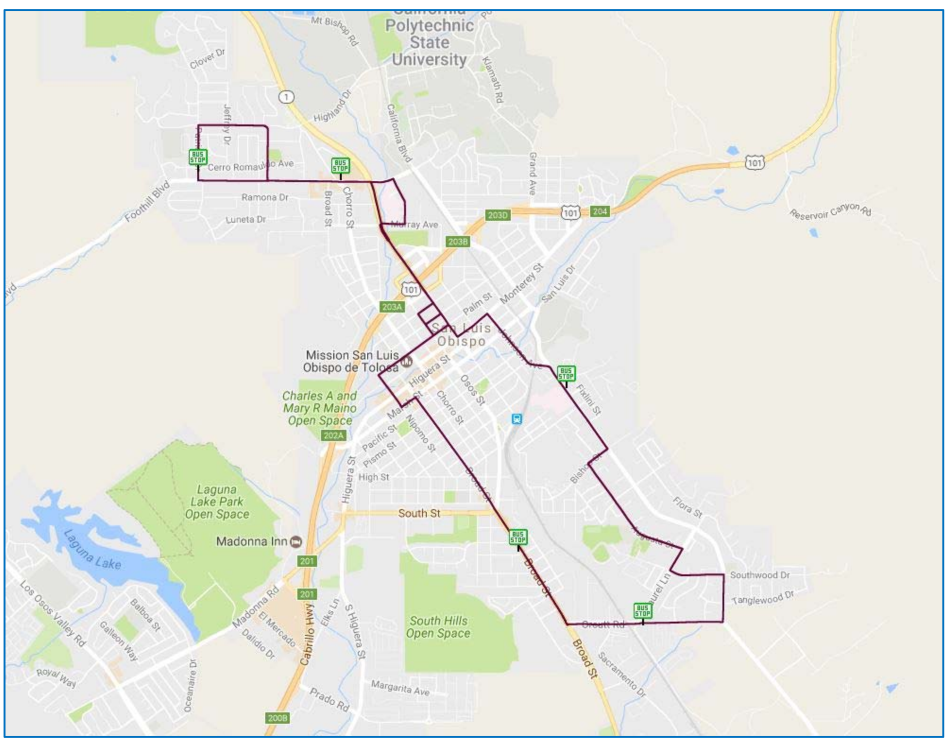


Figure 7: San Luis Obispo Transit Route 2

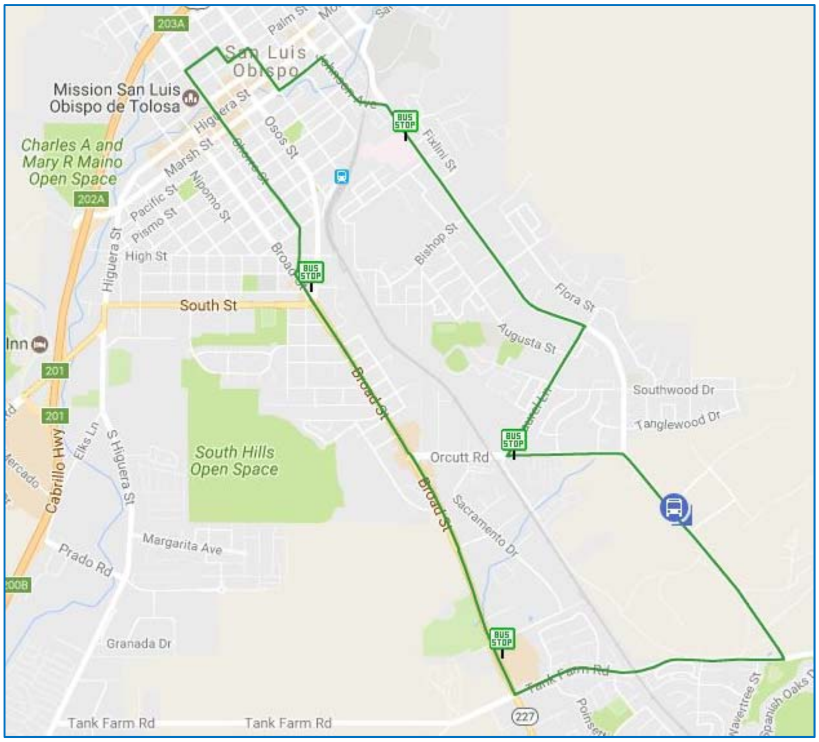


Figure 8: San Luis Obispo Transit Route 3

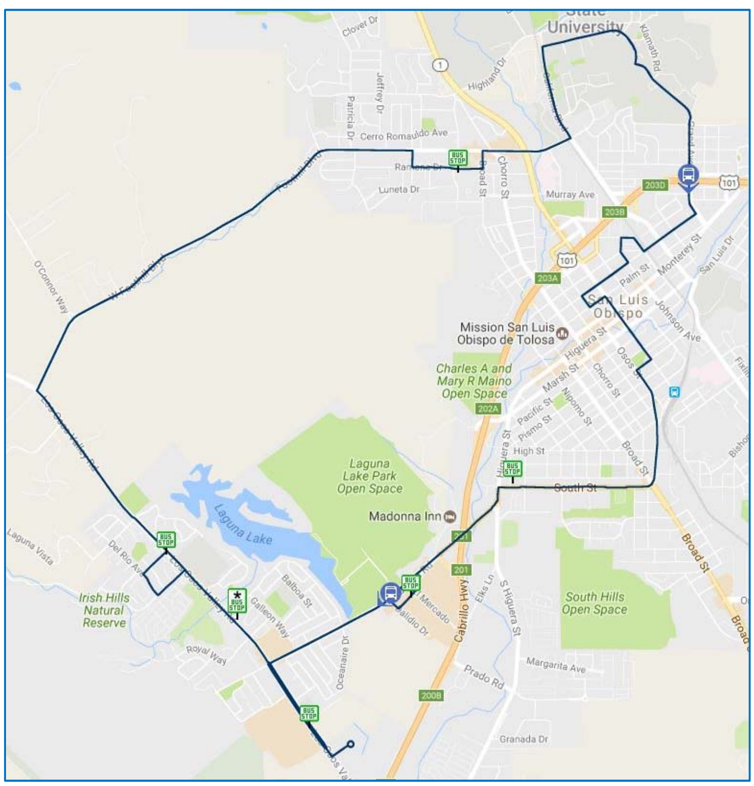


Figure 9: San Luis Obispo Transit Route 4

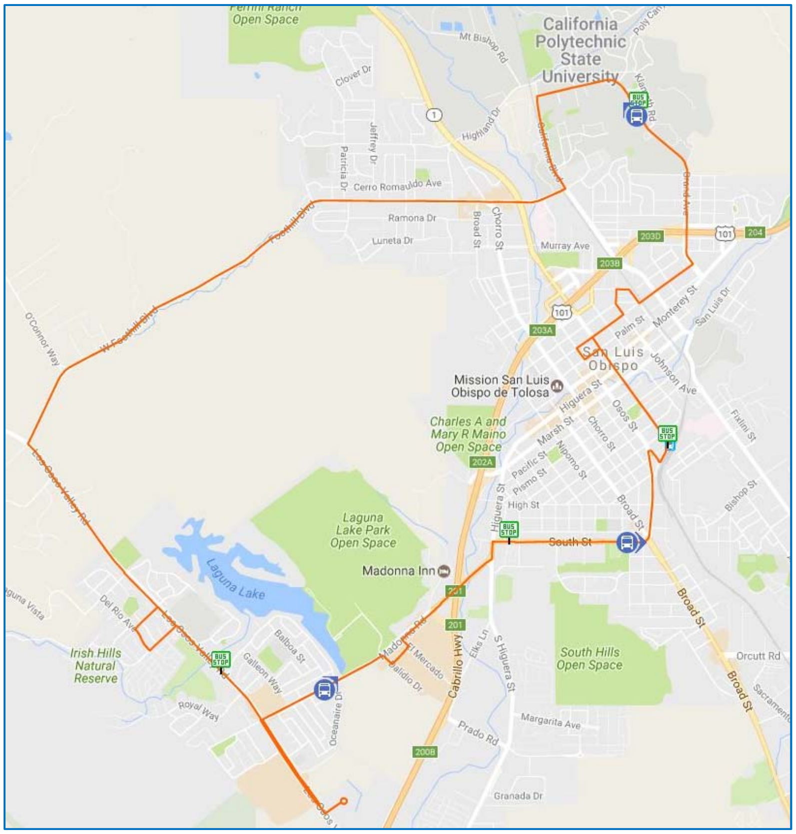


Figure 10: San Luis Obispo Transit Route 5

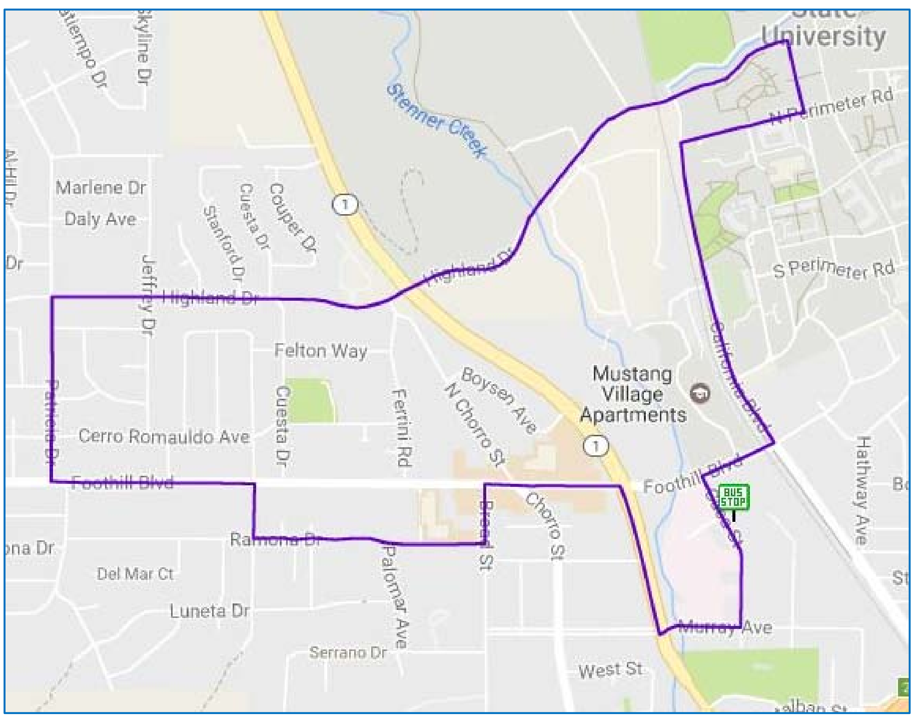


Figure 11: San Luis Obispo Transit Route 6A

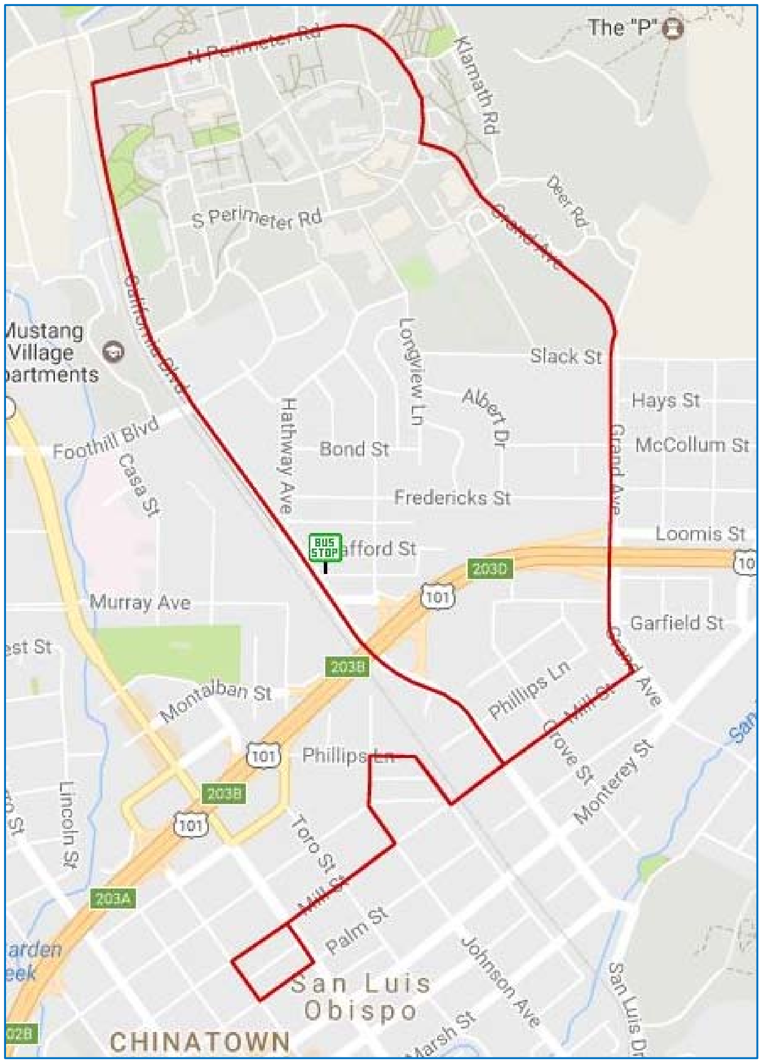


Figure 12: San Luis Obispo Transit Route 6B

3.1.4 BlueMAC Device Installation and Placement

Prior to installation of the BlueMAC devices on the SLO Transit buses, the City of San Luis Obispo Public Works required a written permission and agreement from Cal Poly for release of liability in case an incident relating to the detectors occurs during the data collection period.

BlueMAC devices were installed in five SLO Transit buses. Table 2 shows the bus model, BlueMAC identification number, and route information. Devices were placed on top of the metal electrical box located behind the driver's seat by City of San Luis

Obispo staff, as shown in Figure 15. Devices were placed at this location to connect to the bus for power and to capture Bluetooth signals from boarding passengers. Each device was connected directly to the transit vehicle's power supply through a standard cable, providing continuous power to the detectors during the study. The detectors automatically shut off when the bus was not in operation. As shown in Figure 13, low-energy USB devices were plugged into the USB port of the device to detect a shorter range. The detectors were programmed to detect a thirty-foot radius around the detector, as shown in Figure 14. The BlueMAC detectors were programmed using Class 2 receivers for the 30-foot radius.

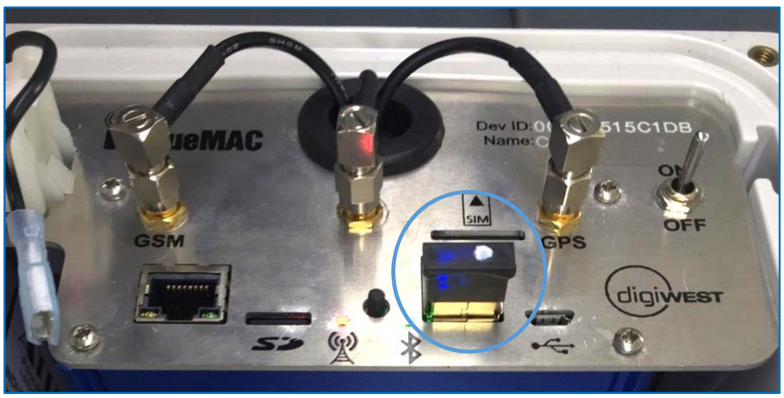


Figure 13: Low-Energy Adapter on the BlueMAC Device

Figure 14: BlueMAC Detection Range

Figure 15: BlueMAC Placement on SLO Transit Bus Number 1264

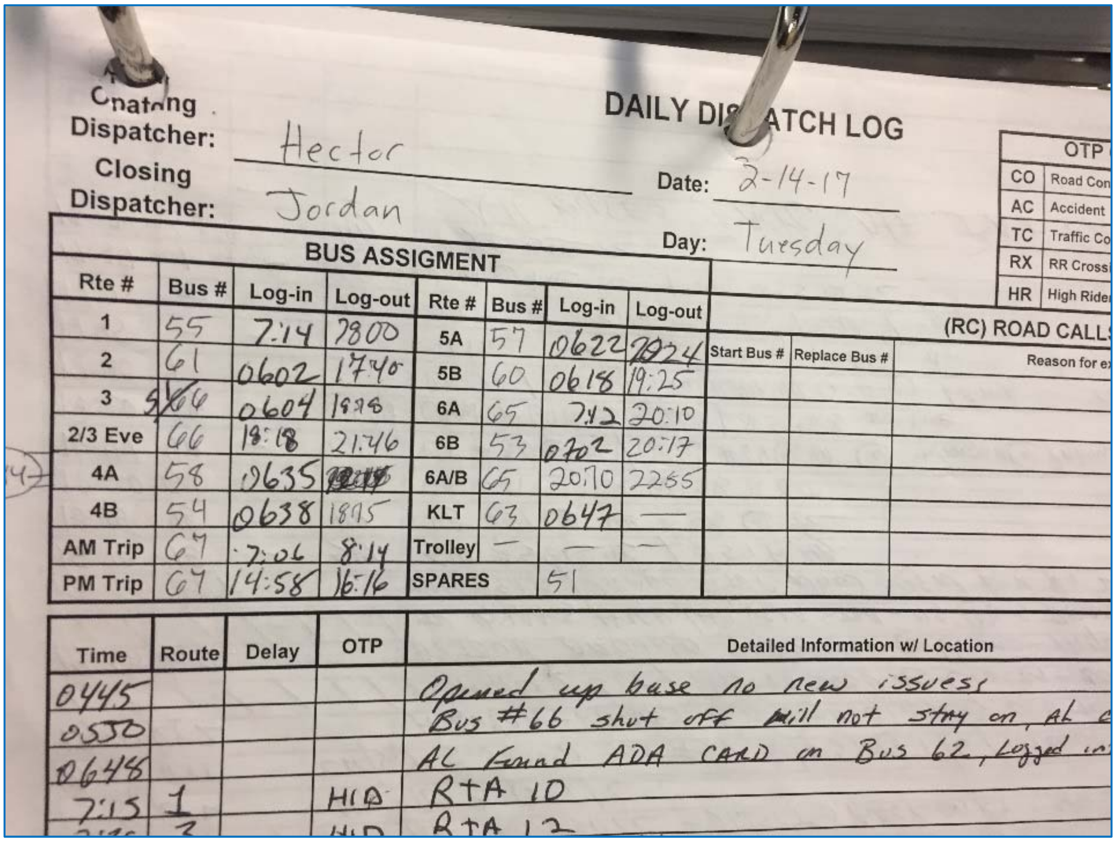
Table 2: BlueMAC Devices and Assigned Bus Number

BlueMAC ID	Bus Number	Make	Model	Year	Length (ft)	Capacity	Fuel
CP-01	858	Gillig	Low Floor	2008	40	36/2 wc	Diesel
CP-02	860	Gillig	Low Floor	2008	40	25/2 wc	Diesel
CP-05	862	Gillig	Low Floor	2008	35	32/2 wc	Diesel
CP-04	1264	Gillig	Low Floor	2012	40	36/2 wc	Diesel
DIGI-150	1365	Gillig	Low Floor	2013	40	36/2 wc	Diesel
*wc=wheelchair							

3.1.5 SLO Transit Route Assignments

Due to scheduled repair and maintenance, the SLO Transit buses switch between routes each day and do not run every day. The assigned bus routes with log-in and log-out times were obtained from Daily Dispatch Logs from SLO Transit, as shown in Figure

16. The summarized table with every observed date and service time is in Appendix D: SLO Transit Weekly Route Assignments.



Opening Dispatcher: Hector

Closing Dispatcher: Jordan

DAILY DISPATCH LOG

Date: 2-14-17

Day: Tuesday

BUS ASSIGMENT

Rte #	Bus #	Log-in	Log-out	Rte #	Bus #	Log-in	Log-out
1	55	7:14	7800	5A	57	0622	2024
2	61	0602	1740	5B	60	0618	19:25
3	5 ~~66~~	0604	1848	6A	65	7:12	20:10
2/3 Eve	66	18:18	21:46	6B	53	0702	20:17
4A	58	0635	[illegible]	6A/B	65	20:10	22:55
4B	54	0638	1815	KLT	63	0647	—
AM Trip	67	7:06	8:14	Trolley	—	—	—
PM Trip	67	14:58	16:16	SPARES		51	

OTP: CO Road Con; AC Accident; TC Traffic Co; RX RR Cross; HR High Rider

(RC) ROAD CALL: Start Bus # | Replace Bus # | Reason for e

Time	Route	Delay	OTP	Detailed Information w/ Location
0445				Opened up base no new issues
0550				Bus #66 shut off will not stay on, AL
0648				AL Found ADA CARD on Bus 62, Logged in
7:15	1		HIA	RTA 10
	3		HIA	RTA 12

Figure 16: SLO Transit Daily Dispatch Log for February 14, 2017

3.2 Data Collection

3.2.1 BlueMAC Sensitivity

The following calculation determines the effective range of the BlueMAC device, according to BlueMAC manufacturer Digiwest.

Responding device T_x power (dBm) + antenna gain (dB_i) – free space loss (dB) – fade margin (dB) + BlueMAC antenna gain (dBi) – cable loss (dB) + device Rx sensitivity (dBm) > 0

The devices have embedded chip antennas and no cables, so antenna gain and cable loss are assumed negligible. Under this assumption, the calculation adjusts to the following:

Responding device T_x power (dBm) – free space loss (dB) – fade margin (dB) + BlueMAC antenna gain (dB_i) – cable loss (dB) + device Rx sensitivity (dBm) > 0

3.2.2 BlueMAC Data Collection

Five BlueMAC detectors were deployed on five different SLO Transit buses on February 13, 2017 and continuously collected data from February 21, 2017 to March 31, 2017 for 38 days' worth of data. An example of the data collected by the BlueMAC devices is shown in Figure 17. For this study, Tuesday, Wednesday, and Thursdays were analyzed from February 28 to March 30.

Capture Time	MAC Address	RSSI
3/21/2017 5:38	3893EB	-86
3/21/2017 5:38	3893EB	-86
3/21/2017 5:38	3893EB	-86
3/21/2017 5:38	3893EB	-86
3/21/2017 5:38	3893EB	-86
3/21/2017 5:38	3893EB	-86
3/21/2017 5:38	3893EB	-78
3/21/2017 5:38	3893EB	-78

Figure 17: BlueMAC Raw Data Example

The capture time is the time the BlueMAC detected a mobile device, the MAC address is the unique six digit identification for each mobile device, and the RSSI is the signal strength from the device. The RSSI number was not used in this study because it was not needed. Only the time stamp of the detection and the MAC addresses were retained.

For maintenance and gas mileage reasons, the SLO Transit buses rotate between routes on a daily or weekly basis. The following routes had at least two consecutive days on Tuesday, Wednesday, and Thursday. The route assignments for each bus were provided by SLO Transit in the form of the Daily Dispatch logs. The BlueMAC data was downloaded and analyzed under the following dates in Table 3.

Table 3: BlueMAC Devices and Assigned Bus Number

Week 1		
2/28/2017	**3/1/2017**	**3/2/2017**
2	2	2
4A	4A	4A
5A	5A	5A
6B	6B	6B
Week 2		
3/7/2017	**3/8/2017**	**3/9/2017**
2	2	-
3	3	3
5A	5A	5A
6B	6B	6B
Week 3		
3/14/2017	**3/15/2017**	**3/16/2017**
2	2	2
4B	4B	4B
6A	6A	6A
Week 4		
3/21/2017	**3/22/2017**	**3/23/2017**
4A	4A	4A
5B	5B	5B
Week 5		
3/28/2017	**3/29/2017**	**3/30/2017**
5A	5A	-
6A	6A	6A

Table 3 defines the names of the weeks of the study. The week number corresponds to the Tuesday, Wednesday, and Thursday dates of the study.

Of the data collection period from February 28 to March 30, there were no severe weather conditions reported during the study period (Weather History for KSBP, 2017). During Week 4 of the study period, Winter Quarter finals were occurring at Cal Poly. Week 5 of the study period was spring break for Cal Poly.

The data collected during the study period contains a significant amount of noise, inconsistencies, and miscellaneous data. For example, at a bus stop, the Bluetooth signals from non-passengers near the bus may be detected. The data was processed with the intention of eliminating the unnecessary data, retaining the onboard detections, and resulting in a filtered data set. The data processing is described in Chapter 4: Results.

3.2.3 GPS Probes

Probe tests were conducted for three bus trips in the week of March 2017 to ensure the Bluetooth detectors were functioning. Three probe runs were completed on the corridor during the weekday PM peak period as a passenger on the SLO Transit bus. The trips were tracked with the GPS Tracking application "myTracks." MyTracks recorded probe runs for comparison to the BlueMAC Bluetooth data. An example of the myTracks data is shown below in Table 4.

Table 4: Geo Tracker Raw Data Example

type	Day	Time	Latitude	Longitude	Altitude (ft)	Speed (mph)	Distance (mi)
T	3/21/2017	0:05:51	35.30239678	-120.6633087	334.9	0	0
T	3/21/2017	0:05:52	35.30240879	-120.6632987	334.9	3.6	5.29
T	3/21/2017	0:05:53	35.30241623	-120.663488	373.1	38.5	56.41
T	3/21/2017	0:05:55	35.30237788	-120.6633828	330.1	11.7	34.28
T	3/21/2017	0:05:56	35.30237784	-120.6633818	330.1	0	0
T	3/21/2017	0:06:03	35.30235881	-120.6633252	330.8	1.8	18.24
T	3/21/2017	0:06:04	35.30236065	-120.6632991	332.9	5.3	7.79
T	3/21/2017	0:06:05	35.30235579	-120.6632836	336.4	3.4	4.94

During the probe run, an iPhone 6 and a 13-inch MacBook Pro were Bluetooth-enabled. The iPhone recorded the GPS tracking and both devices were used to connect to the BlueMAC devices. The MAC IDs were obtained from the "Settings" of each device. The MAC IDs were searched in the raw BlueMAC data. However, neither device was

found in the data on all four probe runs. From the challenges in detecting the personal devices, it was decided to use the APC data as the "ground truth."

3.3.4 Automatic Passenger Counter Data

Bluetooth data was retrieved from the BlueMAC detectors, and APC data was retrieved from Bishop Peak Technology and SLO Transit. Bishop Peak Technology works with SLO Transit in developing and maintaining its SLO Transit mobile phone app and online bus tracker. The app and online bus tracker provide real-time transit schedules, route, and stop data.

APC devices are permanently attached to the front and back doors of the SLO Transit buses. The devices count the passengers boarding and alighting the bus by detecting their movements. Figure 18 shows the APC device on the front door of a SLO Transit bus.

Figure 18: APC Counters on a SLO Transit Bus

The reports provided by SLO Transit include the Hourly APC by Route, Hourly APC by Route and Stop, and APC Events by Route and Stop. The SLO Transit website provides the option of the start and end dates for the APC data. For the Farmer's Market

APC data comparison, Hourly APC by Route files were downloaded separately for Tuesday, Wednesday and Thursday. Table 5 below shows an example of hourly APC data for route and stop for Week 1 of the data collection.

Table 5: Hourly APC by Route and Stop for Week 1, Route 4

Route ID	Route Name	Stop ID	Stop Name	Hour	Avg CountIn	Avg CountOut	Sum CountIn	Sum CountOut
955	Route 4	49	Foothill at Chorro	6	2	0	4	0
955	Route 4	49	Foothill at Chorro	7	1.6667	1	5	3
955	Route 4	49	Foothill at Chorro	8	5.6667	2	17	6
955	Route 4	49	Foothill at Chorro	9	8.6667	1.3333	26	4
955	Route 4	49	Foothill at Chorro	10	6.6667	0.3333	20	1
955	Route 4	49	Foothill at Chorro	11	7	1.6667	21	5
955	Route 4	49	Foothill at Chorro	12	2.3333	0.6667	7	2

3.3.5 Passenger Survey

In addition to the quantitative data collection, a questionnaire was conducted to collect passengers' feedback about their usage of wireless technologies and their perception of proximity-based technologies. A total of 100 responses from randomly chosen passengers were recorded at various SLO Transit bus stops prior to boarding. The results showed that most passengers used SLO Transit at least twice a day and 45 percent reported to wait between 5 and 15 minutes for the bus to arrive. Figure 19 and Figure 20 show these passenger responses.

The majority of the respondents reported use of their devices while waiting for the bus. Overall, 98 respondents claimed to use their devices while waiting or riding the bus, or both. Of the respondents who use devices, 16% use their devices for messaging purposes, 1% for making phone calls, 39% for entertainment, 13% for online access, and 32% for all of the above. Most responders had Bluetooth capable devices, and 27% had their Bluetooth set to discoverable. Of those who disabled their Bluetooth, 1% claimed security concerns, 48% claimed power consumption concerns, and 50% claimed no reason or need for the discoverable setting. Figures 21 and 22 show these passenger survey responses.

Based on the passenger survey, a key limitation of this system is that it relies on Bluetooth technology which does not capture the entire population. Even though most passengers have a Bluetooth-capable phone, only 27% of the responding passengers activate the functionality, providing data collection opportunities for about one-fourth of the ridership population.

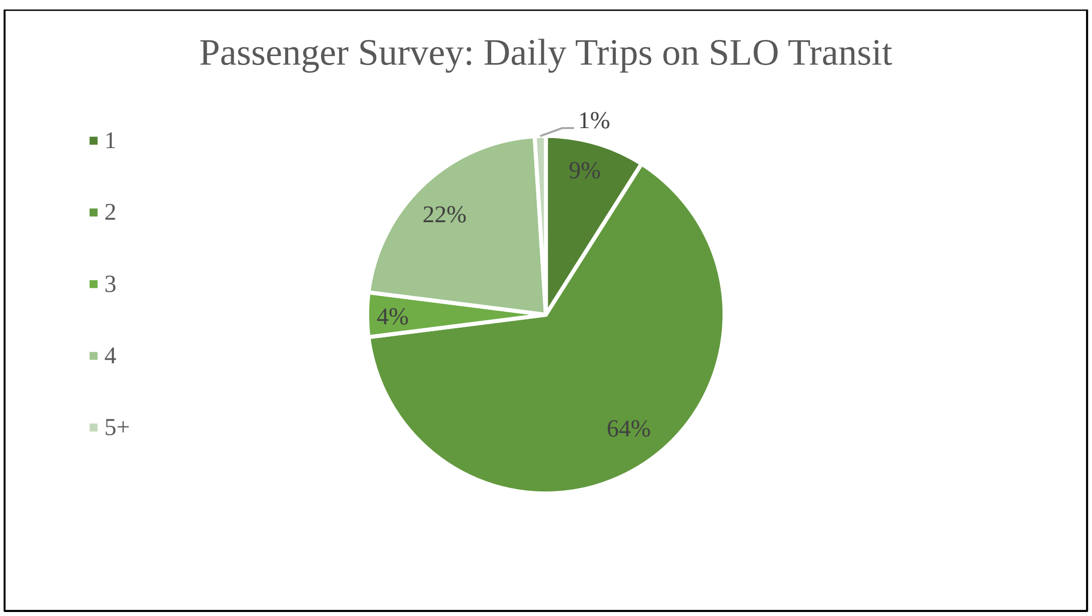


Figure 19: Daily Trips on SLO Transit

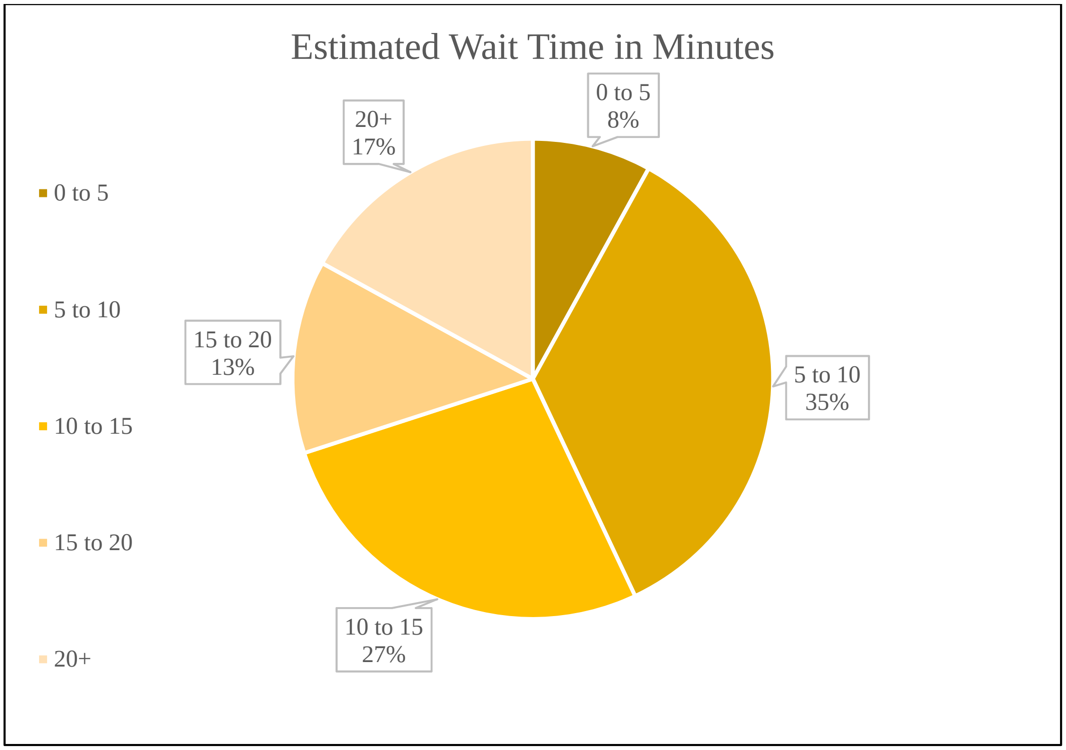


Figure 20: Estimated Wait Time for SLO Transit

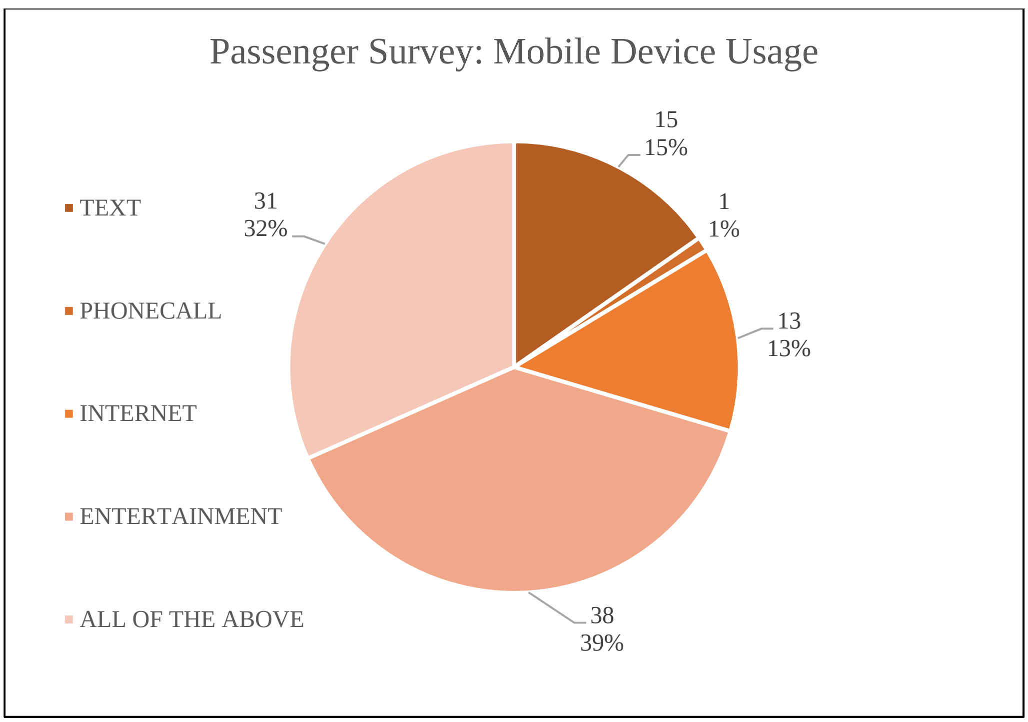


Figure 21: Mobile Device Usage from Passenger Survey

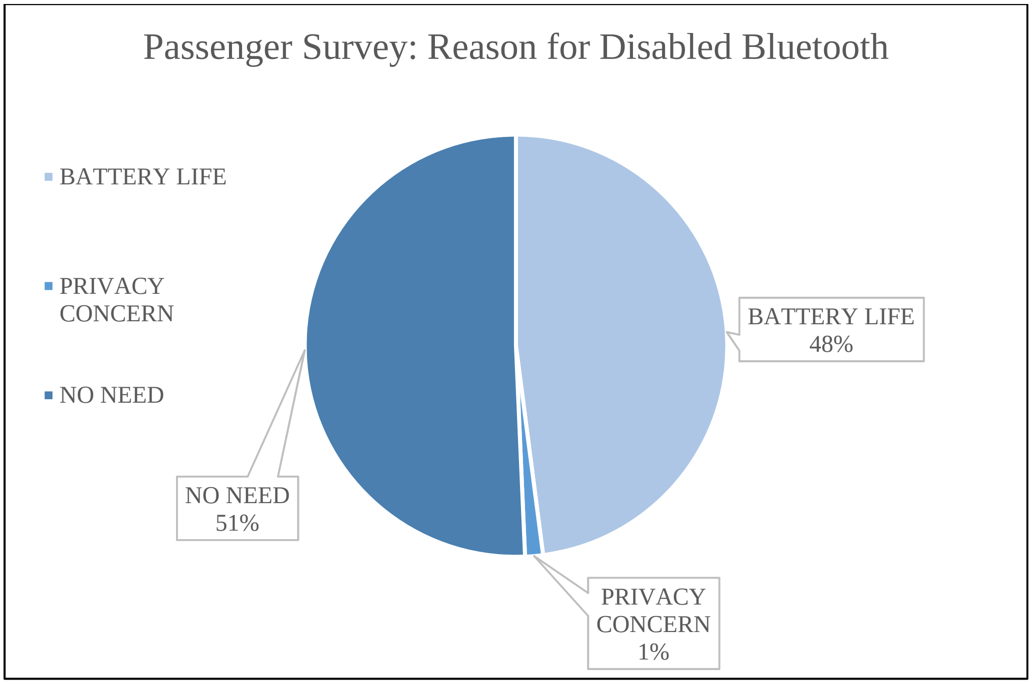


Figure 22: Reason for Disabling Bluetooth from Passenger Survey

3.2.6 Data Collection Cost Comparison

The costs of data collection using BlueMAC, APC, and passenger surveys were compared. A BlueMAC device costs $3,200, and other expenses include $700 towards warranty, cloud service to access data, and cellular access. According to Bishop Peak Technology, the APC hardware and installation costs $1,950 per bus door. SLO Transit buses have two doors, so the cost for APC would be $3,900. Based on the cost estimates, BlueMAC and APC have the comparable costs. The costs during and after the data collection period would incur from the time to analyze, filter, and prepare the report. For passenger surveys, the main costs would be the time to conduct the survey and to process the data. Assuming an hourly cost of $20, the passenger survey would cost $160 for a survey during business hours from 8 AM to 5 PM. The challenges with the passenger survey would involve coordinating surveyors' shifts and locations, compensating for

overtime if necessary, and ensuring that surveyors are punctual to their shifts. The cost of surveys would increase significantly as the desired level of data increases.

3.3 Configuration Tests

Probe runs on the SLO Transit buses were conducted during weekday PM hours on Tuesday, March 21, Thursday, March 23, and Friday, April 28 on Routes 4 and 5. In addition to the myTracks application using GPS to collect travel times and coordinates along the trip, a Bluetooth device with a known MAC address was enabled on the bus to compare GPS times to the BlueMAC detections.

The data is graphed in a time-space diagram, with time on the x-axis and distance on the y-axis. The GPS data for Trial Run #1 is shown in Figure 23.

The slope of the line represents the instantaneous speed (the change in distance/change in time) of the bus. The dashed horizontal lines on the graph show where the bus stopped, such as at a bus stop or an intersection. To validate BlueMAC accuracy, the bus probes should be compared to BlueMAC data where possible. Figures 23, 24, and 25 show the probe runs for Trials 2 through 4. Downtown Transit Center was either the origin or destination of all trips. To determine the bus stop locations, the GPS coordinates from myTracks data were entered on Google Maps and checked for proximity to the scheduled bus stop.

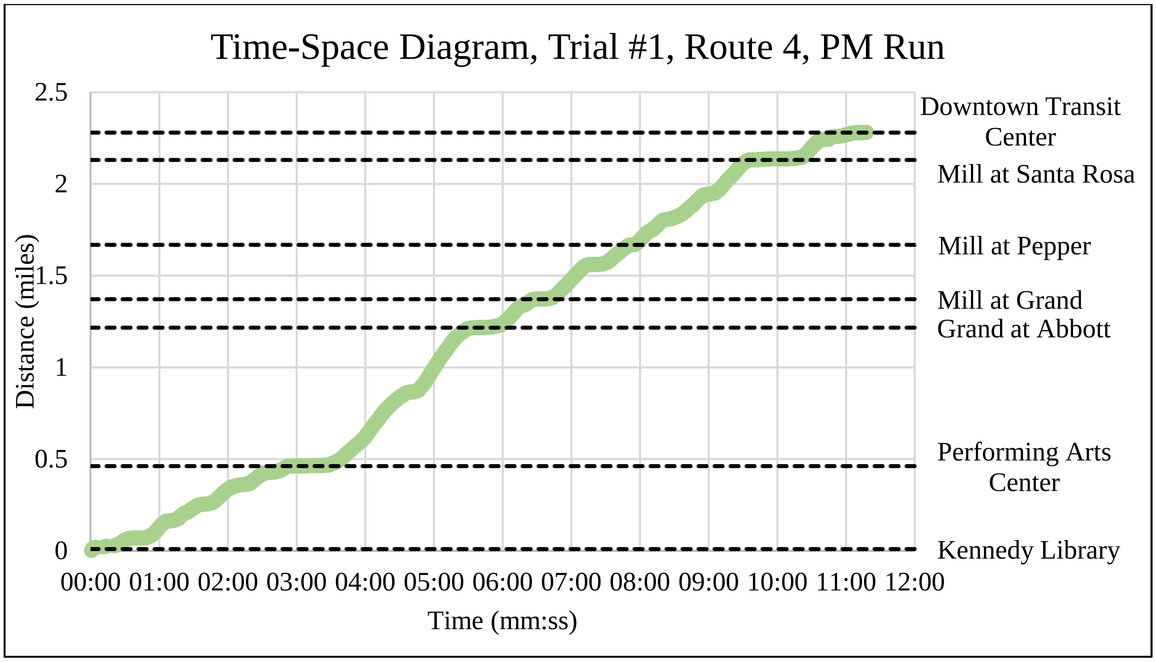


Figure 23: Transit Probe Run #1 Time – Space Diagram

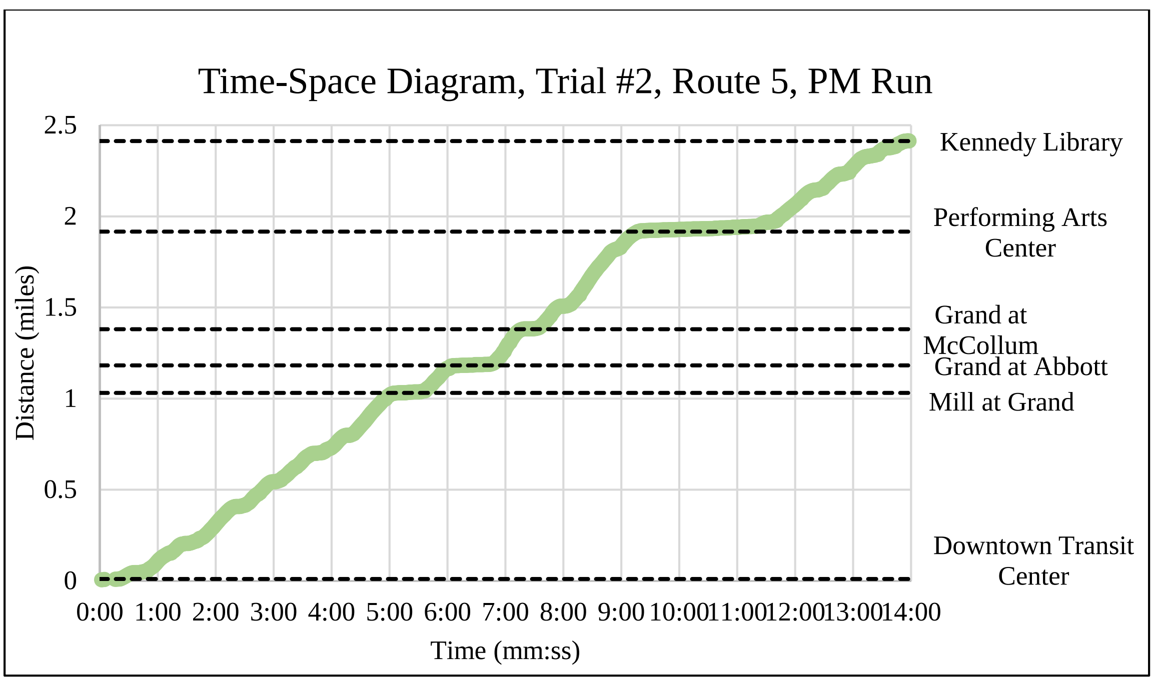


Figure 24: Transit Probe Run #2 Time – Space Diagram

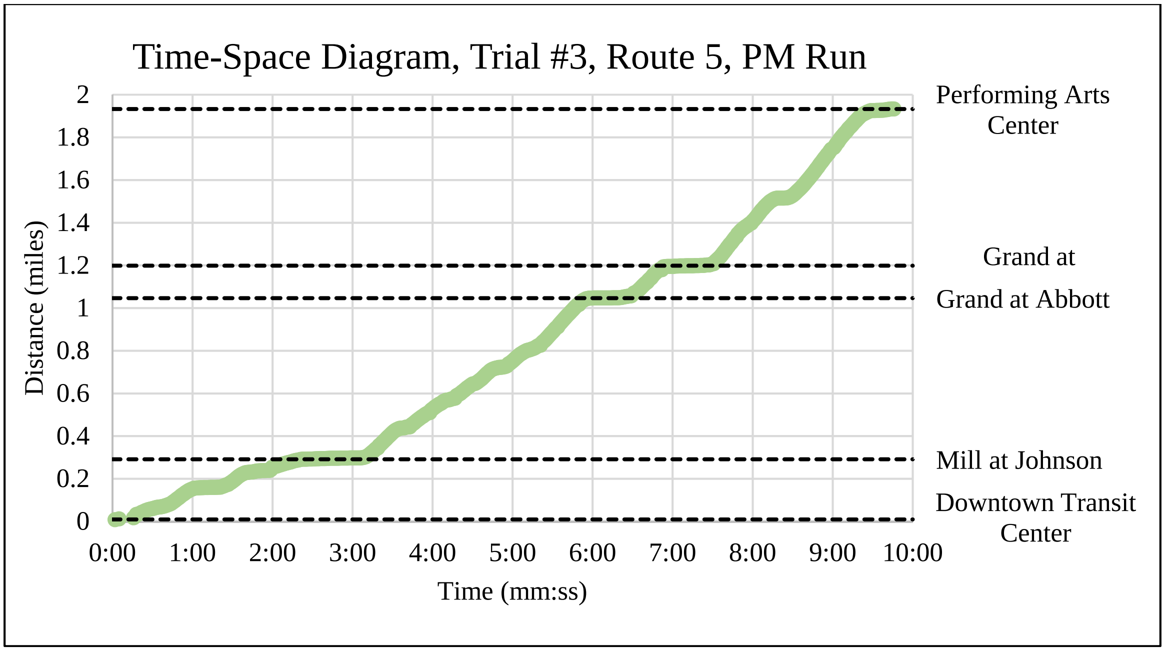


Figure 25: Transit Probe Run #3 Time – Space Diagram

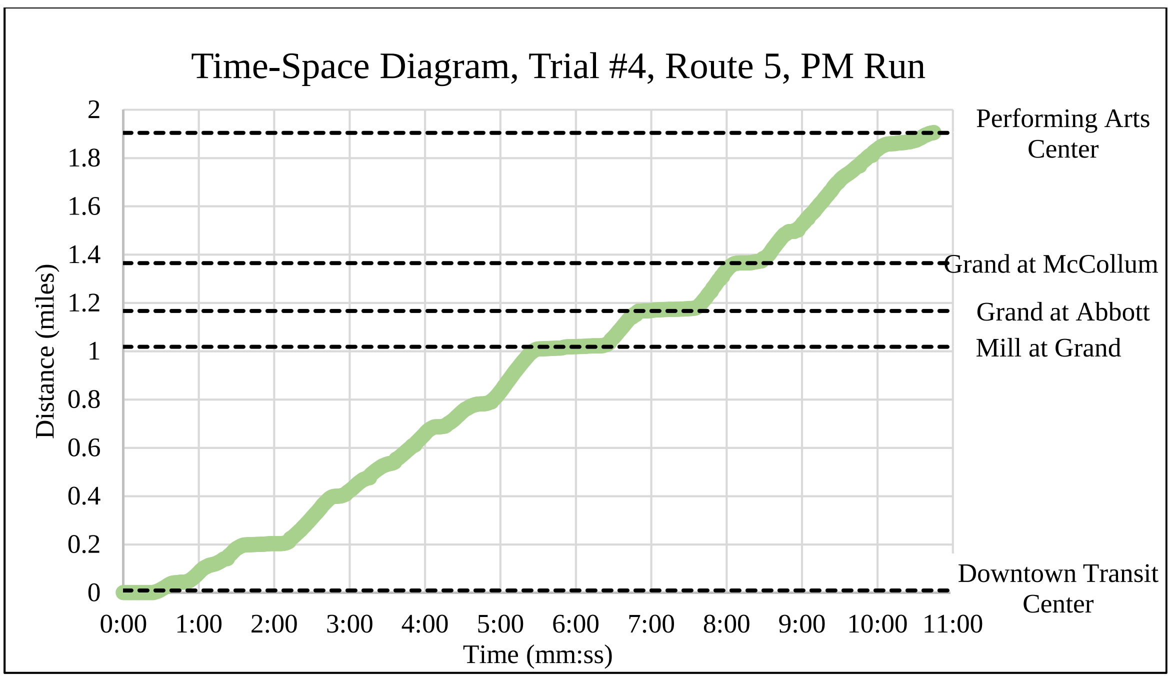


Figure 26: Transit Probe Run #4 Time – Space Diagram

For Trial 1, the personal Bluetooth device was tested on SLO Transit Route 4 from Kennedy Library to Downtown Transit Center on Thursday, March 21, 2017, at 5 PM. A device that was detected for the duration of the trip was plotted with the GPS probe coordinates, as observed in Figure 27.

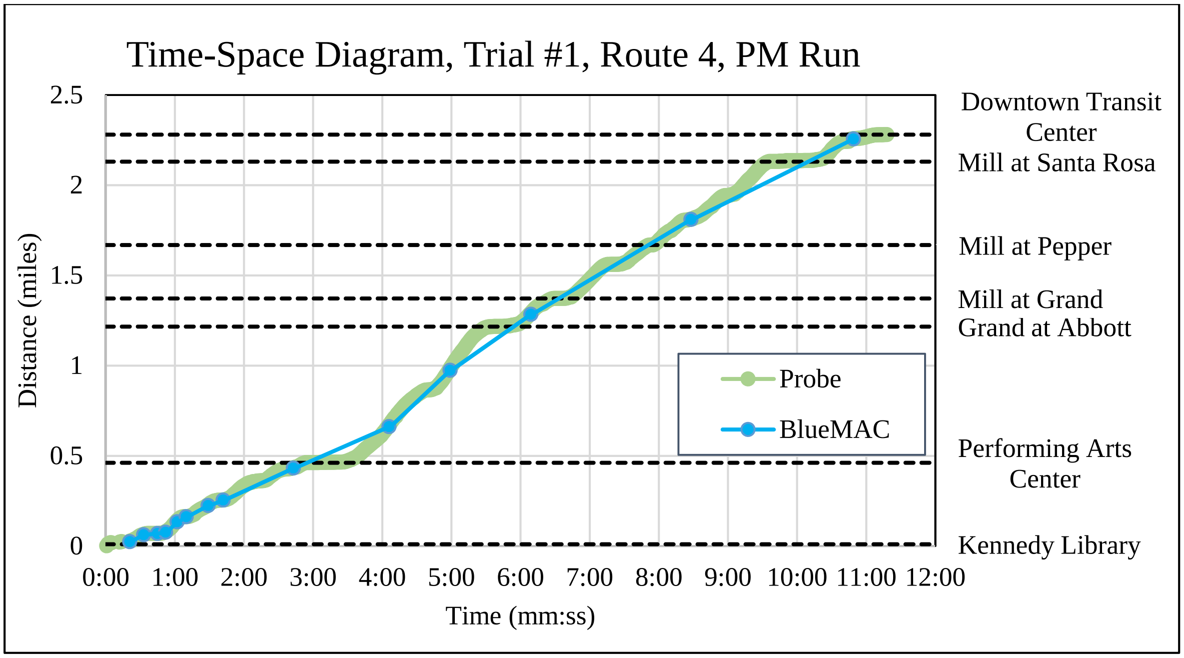


Figure 27: Transit Probe Run # 1 Time-Space Diagram with Bluetooth Detection

3.4 Summary of Research Design and Details

Five BlueMAC devices were deployed on different SLO Transit buses from February to March 2017. The detectors were installed behind the bus driver's seat and connected to the bus power source. The daily assigned routes for each bus were recorded from SLO Transit, then the routes with consecutive Tuesday, Wednesday, and Thursday weeks were binned into projects on the BlueMAC website. APC data was obtained from SLO Transit. Four probe runs using Bluetooth-enabled devices were completed on three separate days in March and April. The challenges with detecting personal devices on the probe runs resulted in using APC data as the "ground truth" to compare to the Bluetooth data.

4. RESULTS

4.1 Data Visualization

Prior to the determination of origin-destination estimates, the data must be filtered and assessed for validity.

4.1.1 Data Organization on myBlueMAC

The data was binned into projects sorted by week and route. For example, Figure 28 is a screenshot from the myBlueMAC website which shows the binned projects for Routes 2, 3, and 4A. The route and week were selected if the detector collected Bluetooth data on Tuesday, Wednesday, and Thursday of that week. The study was set up to automatically download the data files sorted by week – if the data was downloaded by the month, the file would unable to be downloaded due to the large size.

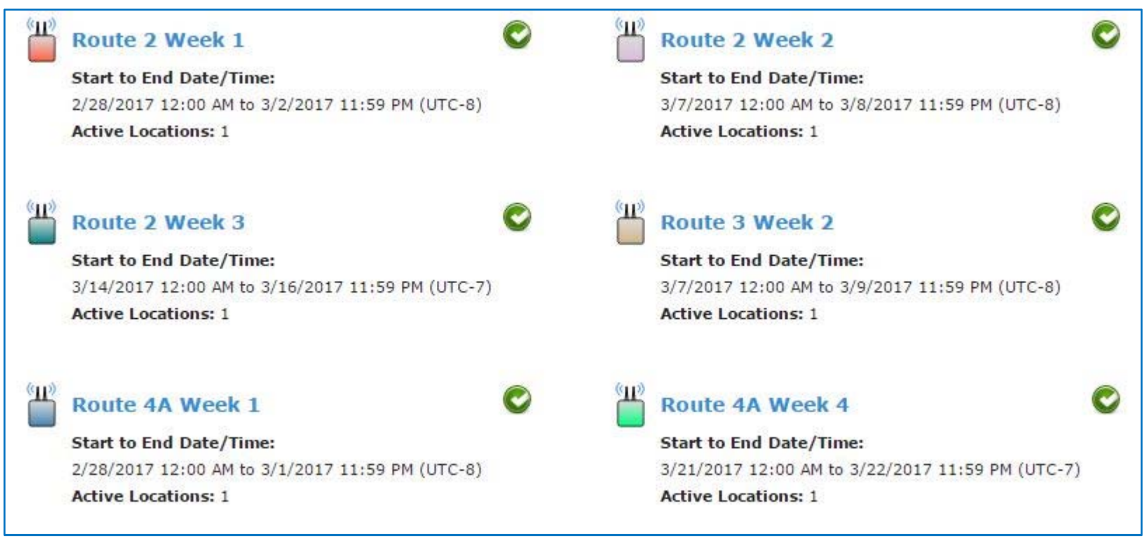


Figure 28: Binned Projects on myBlueMAC

4.1.2 BlueMAC Raw Data

Bluetooth data was collected from February 21, 2017 through March 31, 2017, for a total 38 days. Figure 28 shows an example of raw data collection for device CP-01. The

Capture Rate is the number of unique devices detected per hour. In Figure 29, the y-axis represents the number of unique devices detected.

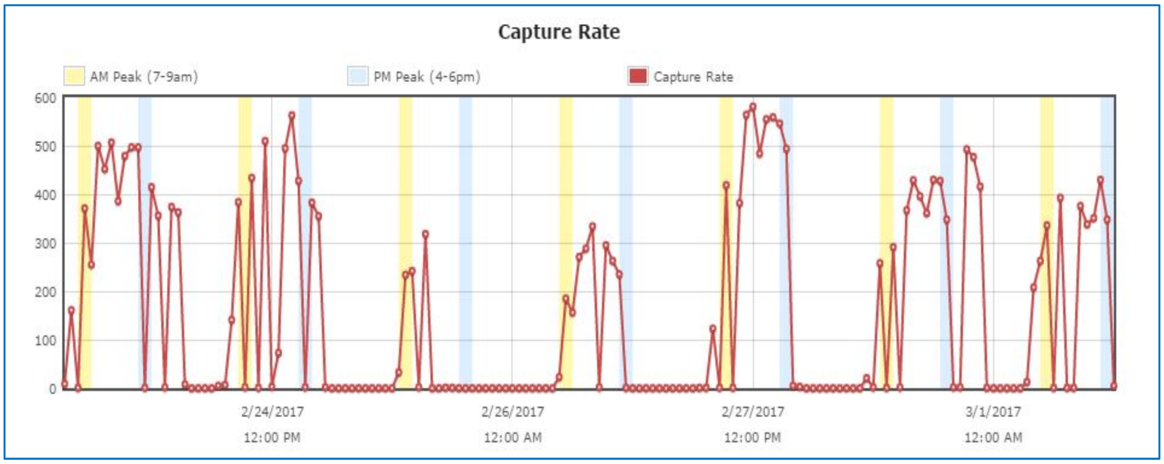


Figure 29: Raw Data Capture Rate Example

Each project provided the Capture Rate as well as the Total Hits and Total Unique Devices per hour. The Total Hits are the number of detections gathered from the devices within range of the BlueMAC detector. The Total Unique Devices are the Bluetooth-enabled devices that were captured within the BlueMAC detector's range. Both the Capture Rate and the Device Counts were accessed on the myBlueMAC website. Figure 30 below shows an example of the number of devices detected for device CP-05 on February 28, 2017.

Start Hour	Total Hits	Total Unique Devices
2/28/2017 5:00 AM	28,395	21
2/28/2017 6:00 AM	64,123	177
2/28/2017 7:00 AM	30,016	258
2/28/2017 8:00 AM	23,612	347

Figure 30: BlueMAC Detector Statistics Example

From the values in Figure 30, the ratios between the Total Hits and Total Unique Devices vary. For example, the Hits to Devices ratio for 6 AM on February 28, 2017, is

362:1 while another pair at 8 AM resulted in a 68:1 ratio. The unpredictable ratios from the detections suggest that the Bluetooth detections vary from factors such as the strength of Bluetooth signal, the range of detection, and physical barriers between the device and the detector such as storage in a purse or pocket. The varying ratios make the number of total hits unpredictable by the hour.

Routes with multiple weeks of data collected for Tuesday, Wednesday, and Thursday were graphed. Figure 31 shows the detected devices on Route 2 for Weeks 1 and 3. On Figure 31, Week 2 is not included because it only accounts for Tuesday and Wednesday. Figure 32 shows the detected devices on Route 5 for Weeks 1, 2, and 4. Figure 33 shows the detected devices on Route 6A for Weeks 3 and 5. Figure 34 shows the detected devices on Route 6B for Weeks 1 and 2. The detected devices within the bus service time frame were counted. The time frames were based on the Daily Dispatch logs provided by SLO Transit.

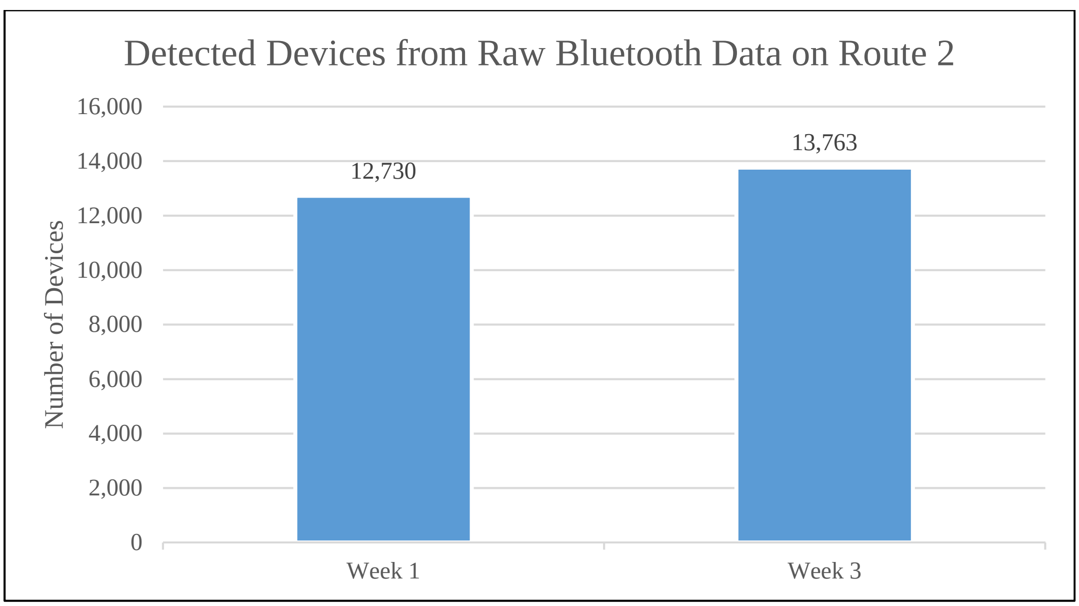


Figure 31: Raw Data Devices Detected Using BlueMAC on Route 2

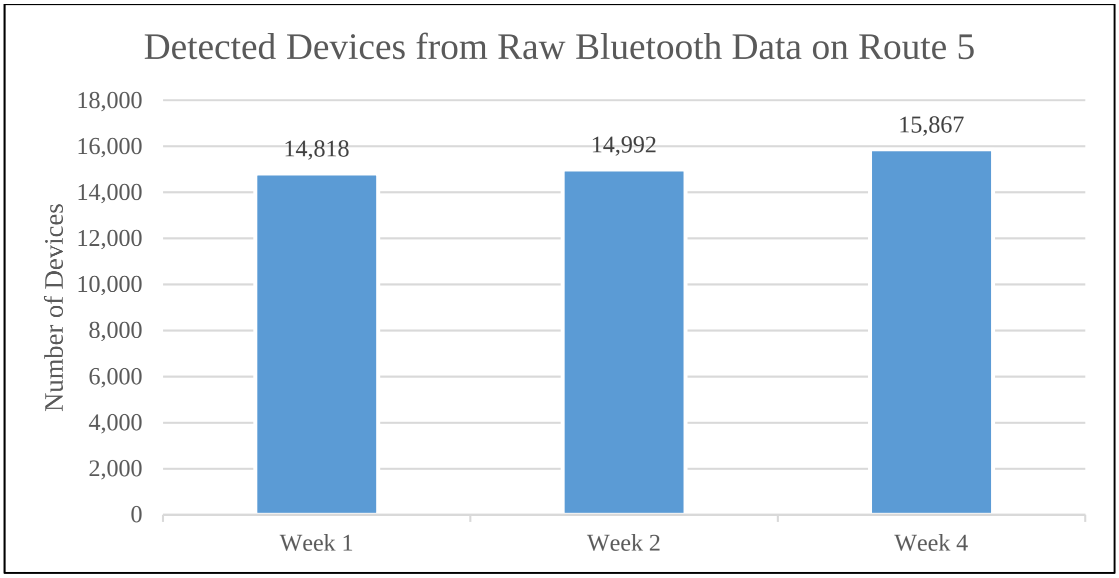


Figure 32: Raw Data Devices Detected Using BlueMAC on Route 5

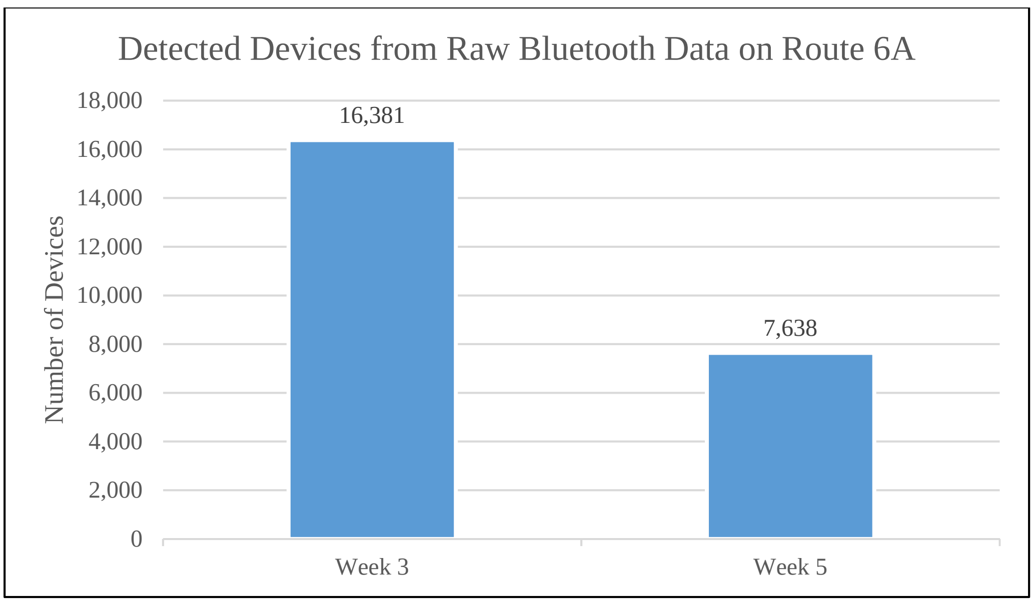


Figure 33: Raw Data Devices Detected Using BlueMAC on Route 6A

It should be noted that Week 4 of the data collection period final exams at Cal Poly San Luis Obispo. Week 5 of the data collection period was spring break for the university, as shown in Figure 33 with the lower detection rates during Week 5 compared to that of previous weeks.

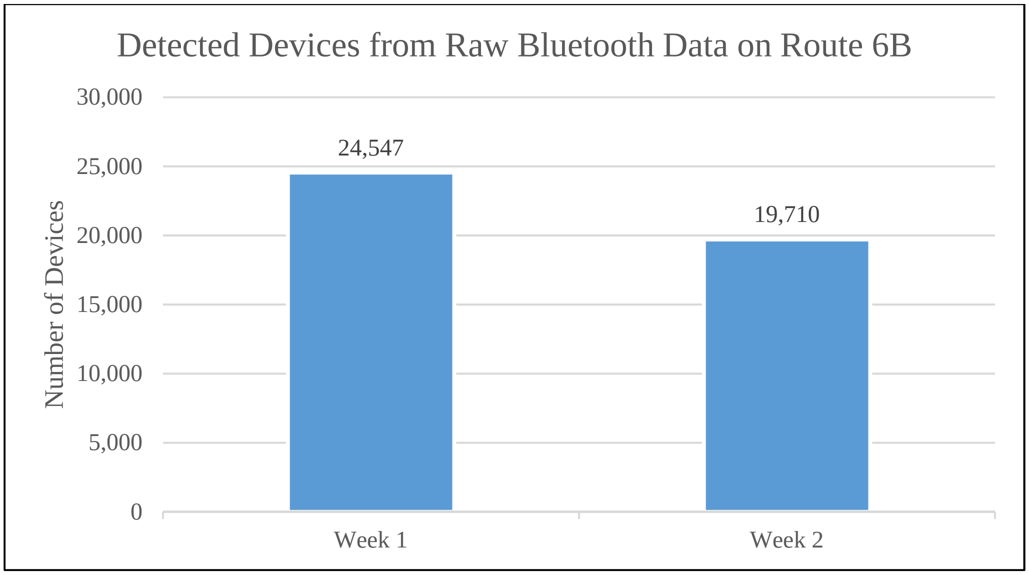


Figure 34: Raw Data Devices Detected Using BlueMAC on Route 6B

4.1.3 Raw BlueMAC Data and Automated Passenger Counter Comparison

During the study, APC data was collected from SLO Transit. The number of APC count in passengers per hour were graphed with the Bluetooth devices detected. Routes 2, 3, and 6A were graphed because only one bus runs per route at a time. These routes have six figures each – two for each day of the week that is Tuesday, Wednesday, and Thursday. For Routes 4 and 5, there are two buses running simultaneously, and the APC data combines the passenger data from the two buses per route, so these routes were not included in the figures. Figures 35 through 43 show the number of unique devices detected versus the APC count per hour. The hours of the graphs represent the bus log in and log out times provided by the SLO Transit Daily Dispatch logs.

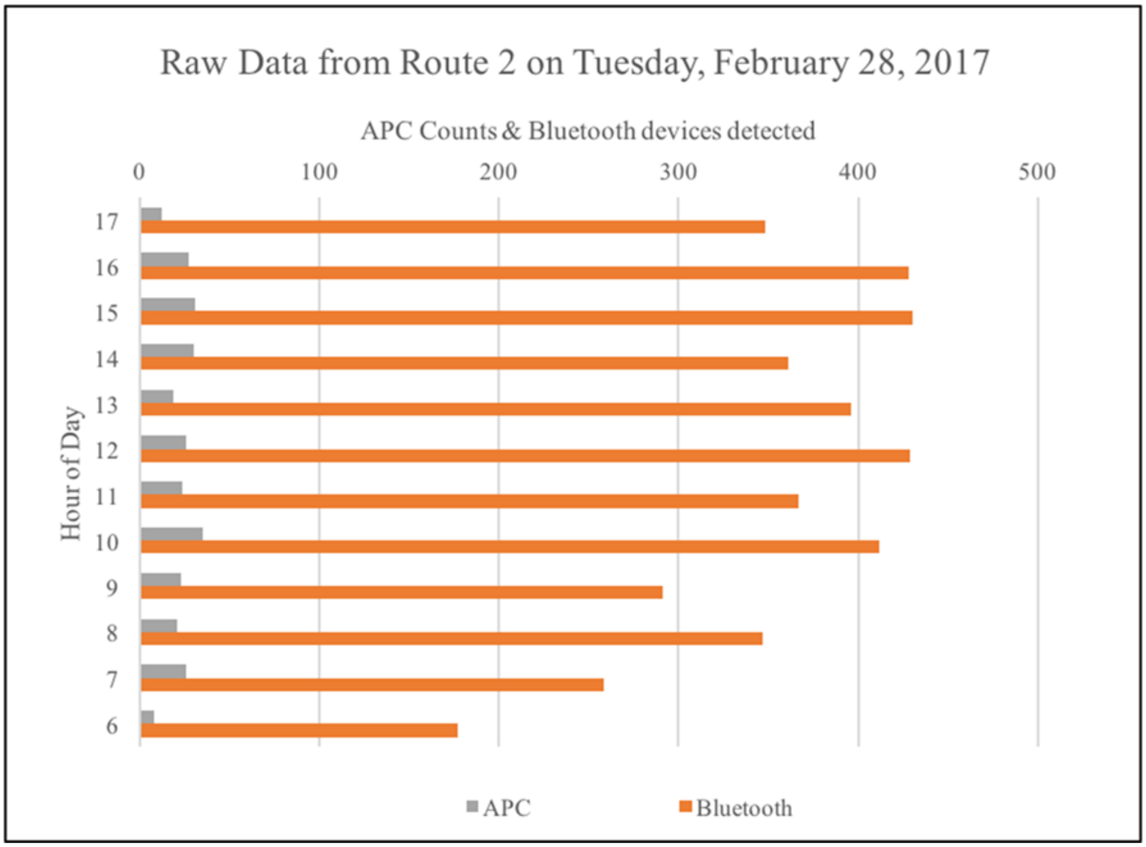


Figure 35: APC Count In and Bluetooth Devices Captured for Route 2 on February 28

Figures 35 shows the data comparison for Route 2 on February 28, 2017. The orange bars in represent the unique Bluetooth devices detected, and the gray bars represent the APC passengers boarding the bus per hour. The correlation between the detected Bluetooth devices and number of passengers boarding based on the automated passenger counter data were graphed. The x-axis represents the Bluetooth devices detected, and the y-axis represents the APC count in. Each data point represents the hour of the day. The correlation graphs are in Appendix C: Hourly Observation Graphs.

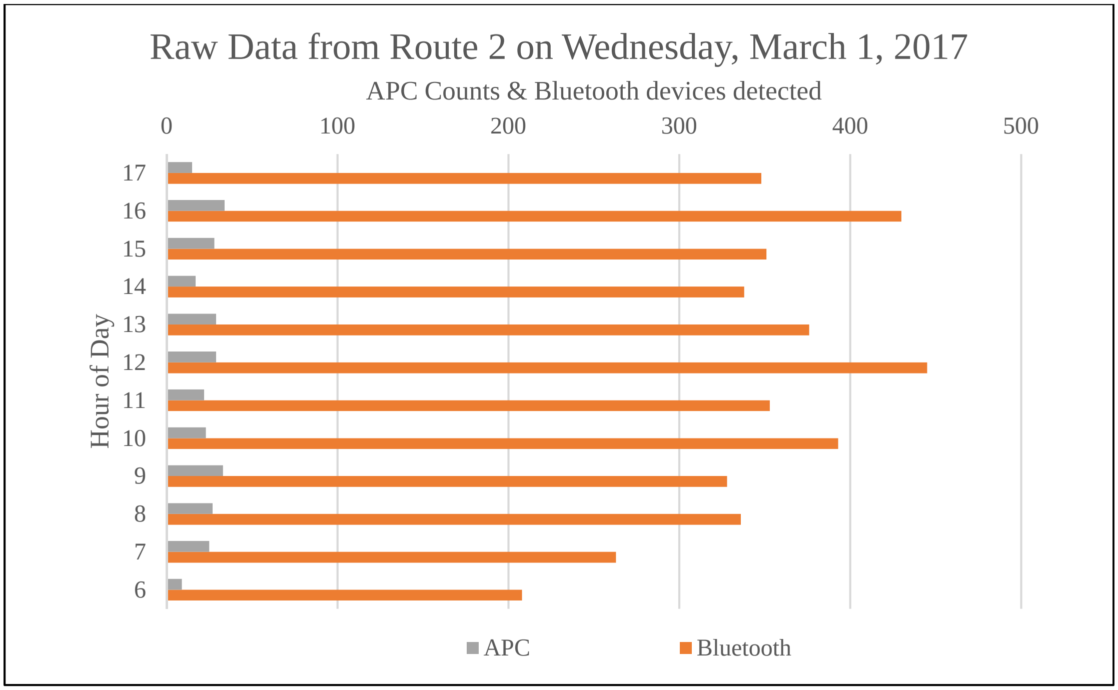


Figure 36: APC Count In and Bluetooth Devices Captured for Route 2 on March 1

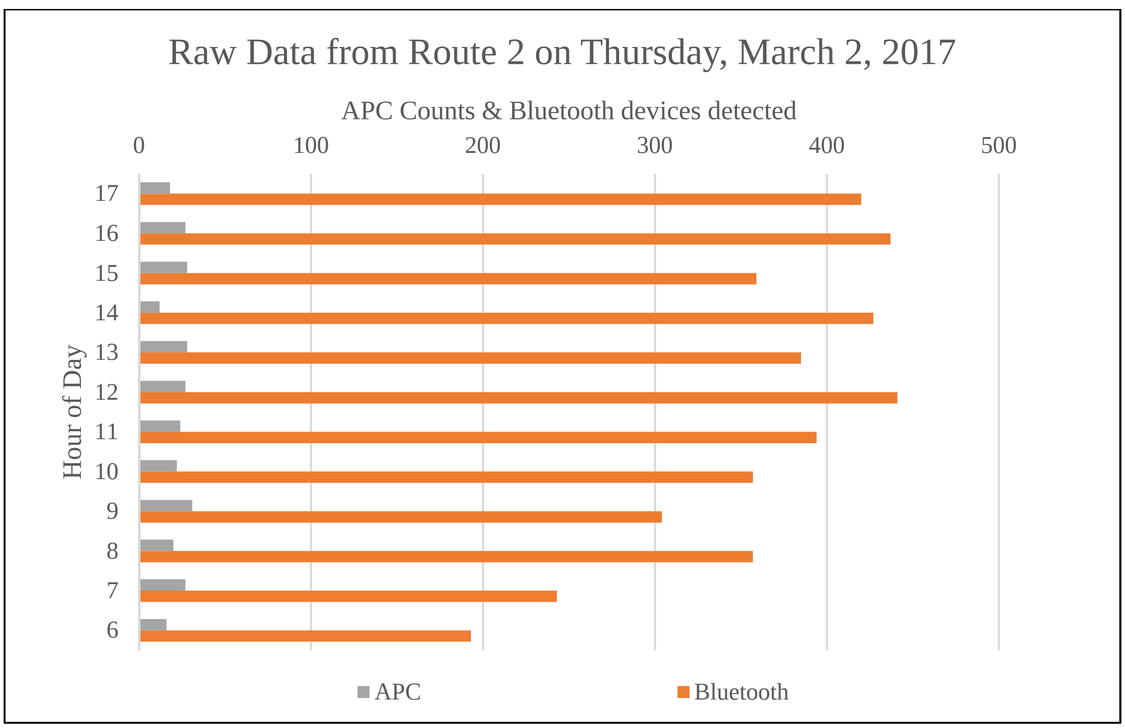


Figure 37: APC Count In and Bluetooth Devices Captured for Route 2 on March 2

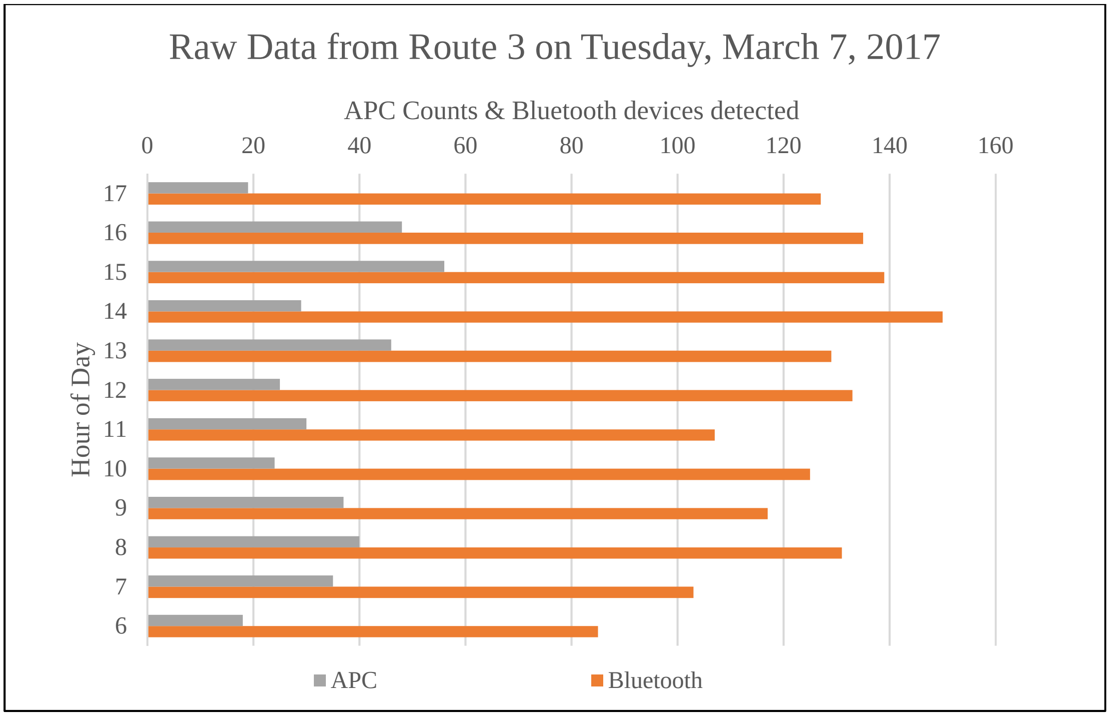


Figure 38: APC Count In and Bluetooth Devices Captured for Route 3 on March 7

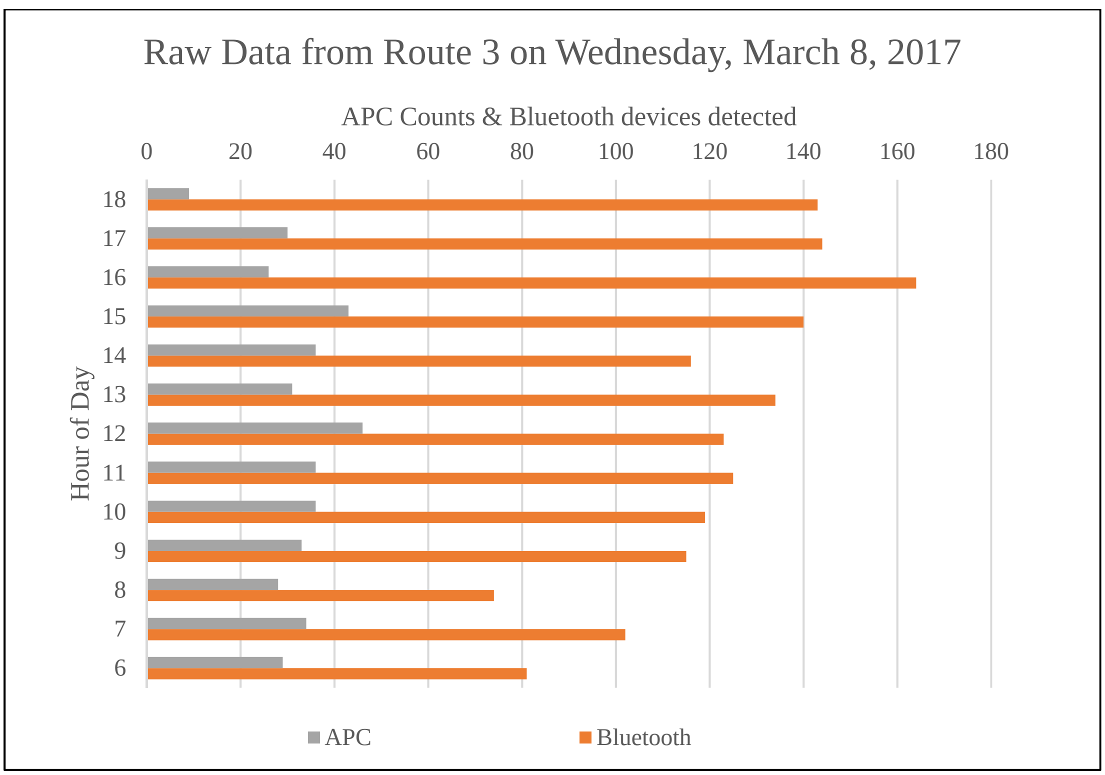


Figure 39: APC Count In and Bluetooth Devices Captured for Route 3 on March 8

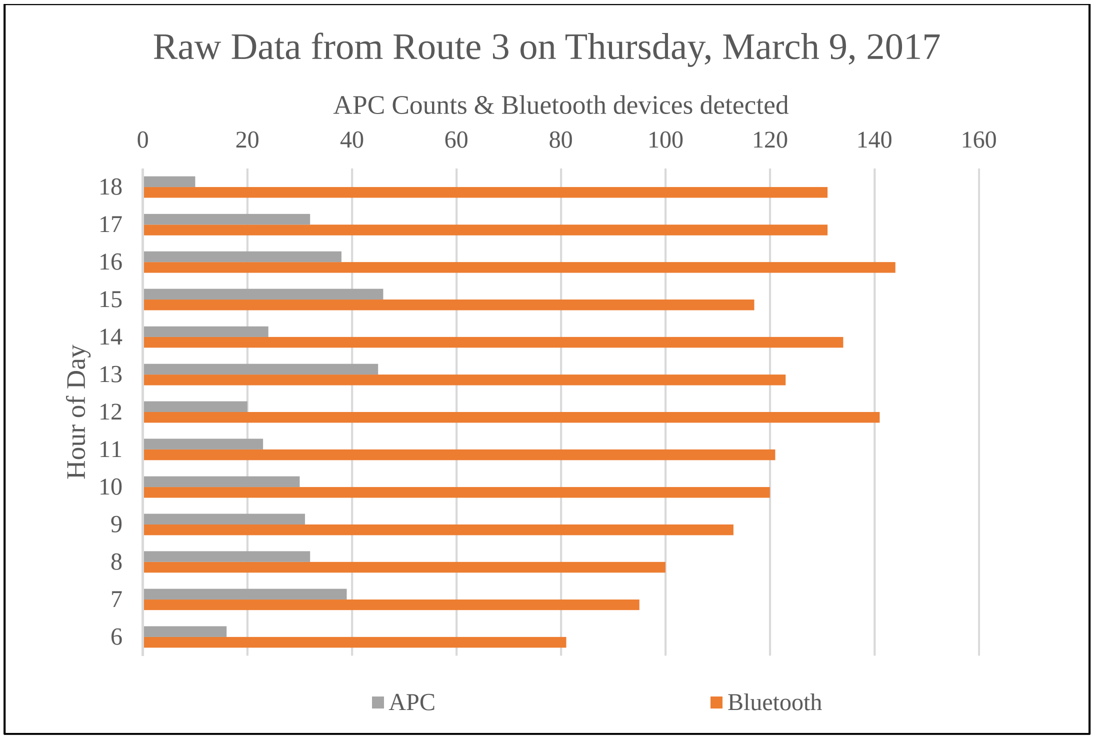


Figure 40: APC Count In and Bluetooth Devices Captured for Route 3 on March 9

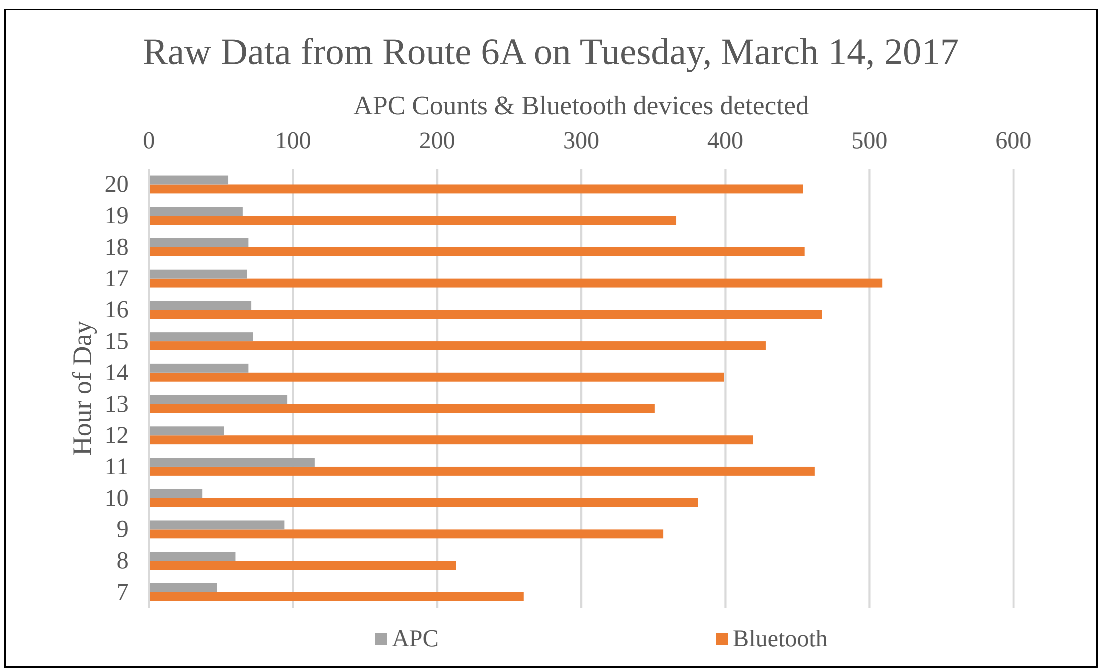


Figure 41: APC Count In and Bluetooth Devices Captured for Route 6A on March 14

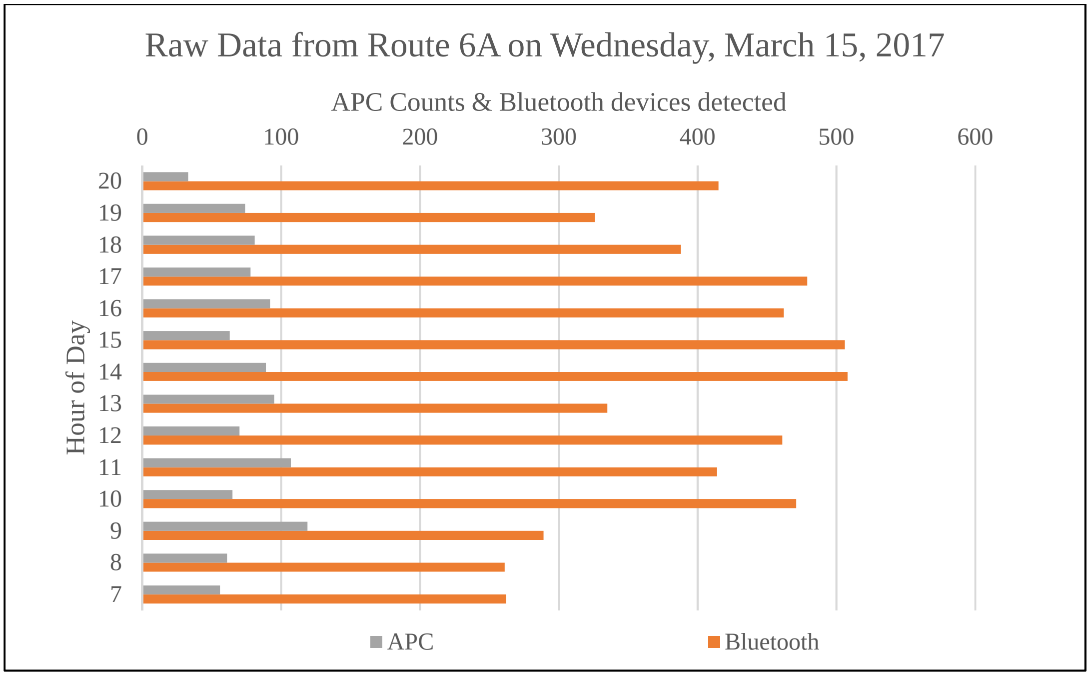


Figure 42: APC Count In and Bluetooth Devices Captured for Route 6A on March 15

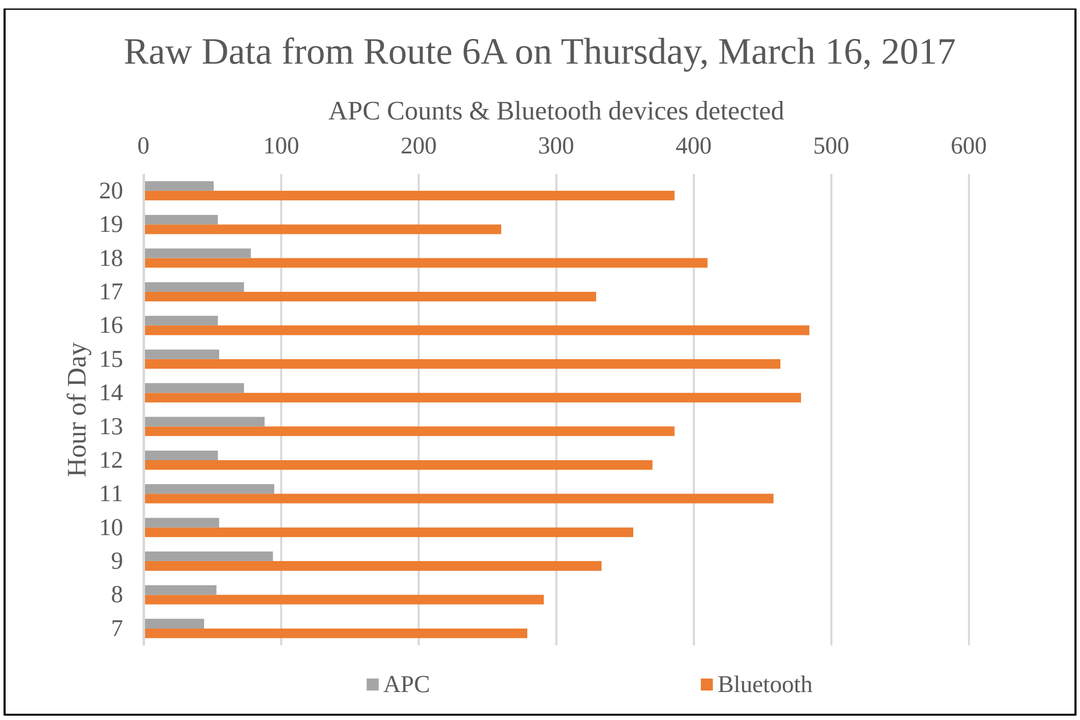


Figure 43: APC Count In and Bluetooth Devices Captured for Route 6A on March 16

Table 6: Summary of Raw BlueMAC Data and APC Data for Routes 2, 3, and 6A

Day	Date	Route	Bluetooth	APC	R^2	Percent Difference
Tuesday	2/28/2017	2	4,244	282	0.3969	-1404.96%
Wednesday	3/1/2017	2	4,169	291	0.3743	-1332.65%
Thursday	3/2/2017	2	4,317	280	0.0000	-1441.79%
Tuesday	3/7/2017	3	1,613	426	0.1147	-278.64%
Wednesday	3/8/2017	3	1,580	417	0.0152	-278.90%
Thursday	3/9/2017	3	1,712	390	0.0928	-338.97%
Tuesday	3/14/2017	6A	5,521	970	0.0517	-469.18%
Wednesday	3/15/2017	6A	4,836	976	0.0022	-395.49%
Thursday	3/16/2017	6A	5,283	921	0.0787	-473.62%
			Average Percent Difference			-712.69%

Table 6 shows the summarized daily counts for Routes 2, 3, and 6A based on Figures 31 through 42. The Bluetooth and APC columns contain the total daily devices detected and the number of passengers boarding the bus. The average percent difference between the daily APC and raw BlueMAC data for the nine days is -712.69%. The comparison of the raw BlueMAC data and the APC data indicates that the extraneous data can be identified and filtered to retain the passenger trips. The high unique devices detected derive from: cars driving past the bus, the bus driver, passengers carrying multiple Bluetooth-enabled devices, or people waiting, walking, or bicycling past bus stops.

4.1.4 Farmer’s Market Analysis Using APC Boarding Counts for Single Days

The APC data was compared specifically for the routes that connect Cal Poly to Downtown San Luis Obispo during PM hours on Thursday nights when the Downtown San Luis Obispo Farmer’s Market occurs. The Farmer’s Market runs from 6 PM to 9 PM. The weekly event attracts Cal Poly students who use SLO Transit to travel from Cal Poly to Downtown and back. The routes analyzed and compared are 4 and 6B. Route 5

connects Downtown San Luis Obispo to Cal Poly, but was not analyzed because the service ends at 7:21 PM on weekdays. The APC data for Tuesday, Wednesday, and Thursday were compared prior to including the filtered BlueMAC data.

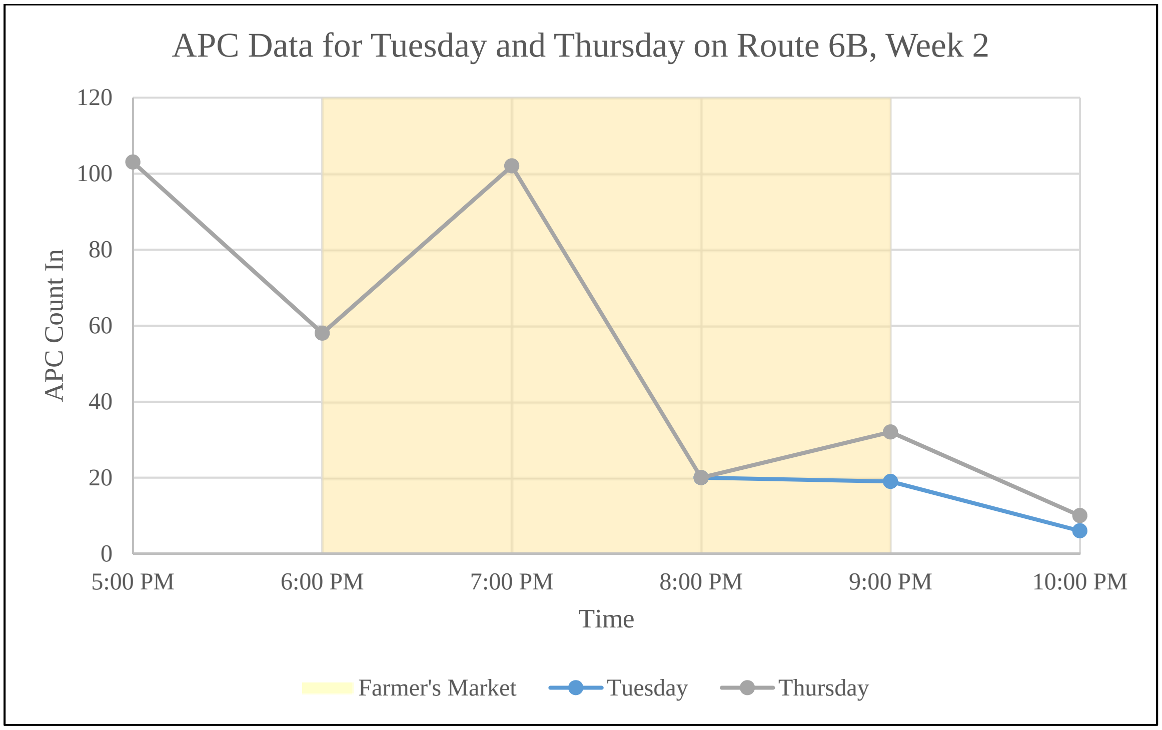


Figure 44: APC Data for Tuesday and Thursday on Route 6B, Week 2

In Figure 44, APC data for Tuesday, March 8 was only available from 8 PM to 10 PM. The data from Figure 43 was collected during Week 2 of the study, so dates are Tuesday, March 7 and Thursday, March 9. The highlighted area on the graph shows the time frame of the San Luis Obispo Downtown Farmer's Market which is 6 PM to 9 PM. Route 6B runs as a loop connecting Cal Poly to Downtown San Luis Obispo. The higher APC count in at 7 PM on Thursday could account for students going home from classes and students going to Farmer's Market from Cal Poly.

Figure 45 below shows the APC data for Route 4 on Tuesday, Wednesday, and Thursday of Week 3 of the observation period. Route 4 serves as a loop around the city, and provides trips from Cal Poly to Downtown. APC data for Wednesday was available

up to 6 PM. There is slightly higher ridership on Thursday than on Tuesday during the Farmer’s Market time period.

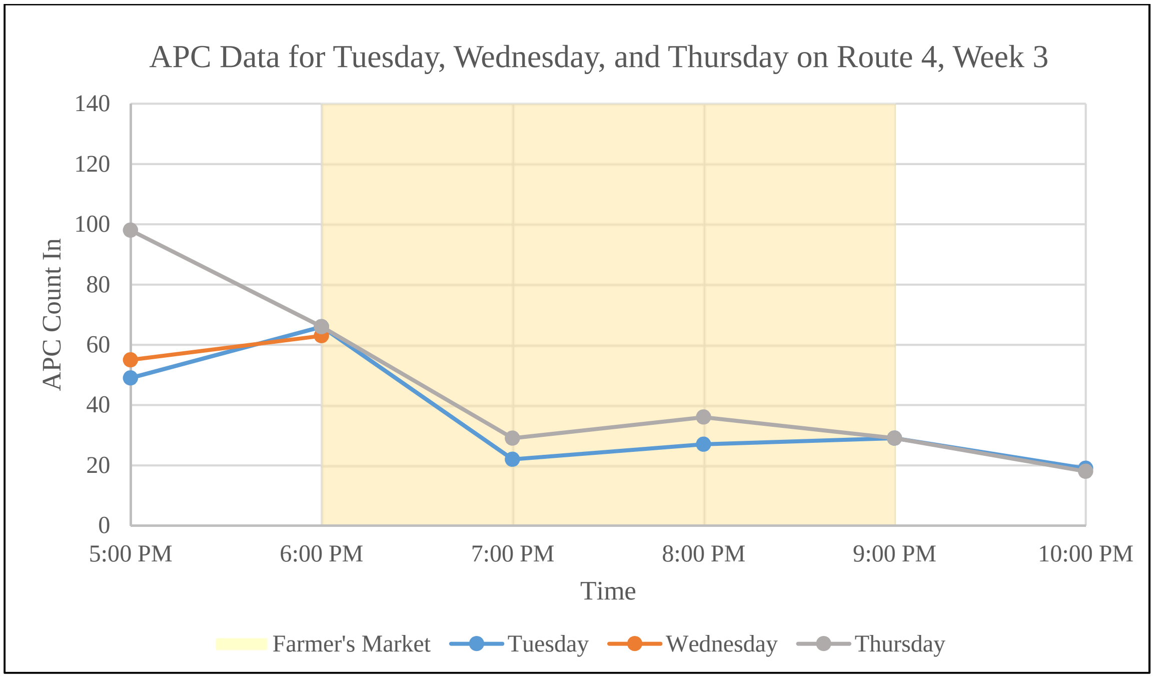


Figure 45: APC Data for Tuesday, Wednesday, and Thursday on Route 4, Week 3

4.1.5 Farmer’s Market Analysis Using APC Boarding Counts for Multiple Days

After graphing Route 4 and 6B for only one Tuesday and one Thursday, multiple days were pooled to compare Tuesdays and Thursdays. The weather for the selected days was clear, and the Farmer’s Market was held on all the selected Thursdays. Figure 46 shows three Tuesdays (March 14, April 18, and May 9, 2017) and three Thursdays (March 16, April 20, and May 11, 2017) with combined passenger counts for Route 6B. The combined passenger counts on Thursdays were consistently higher than the passenger counts on Tuesdays, indicating the higher ridership during Farmer’s Market times. The combined ridership during the Tuesday from 5 PM to 10 PM of 664 passengers saw a 55% increase to 1,031 passengers during the same hours on Thursday PM hours. The ridership during Thursday PM hours peaked at 333 passengers at 7 PM,

which was expected from students riding the bus from Cal Poly to Downtown for Farmer's Market. During Tuesday PM hours, the ridership peaked at 199 passengers at 6 PM.

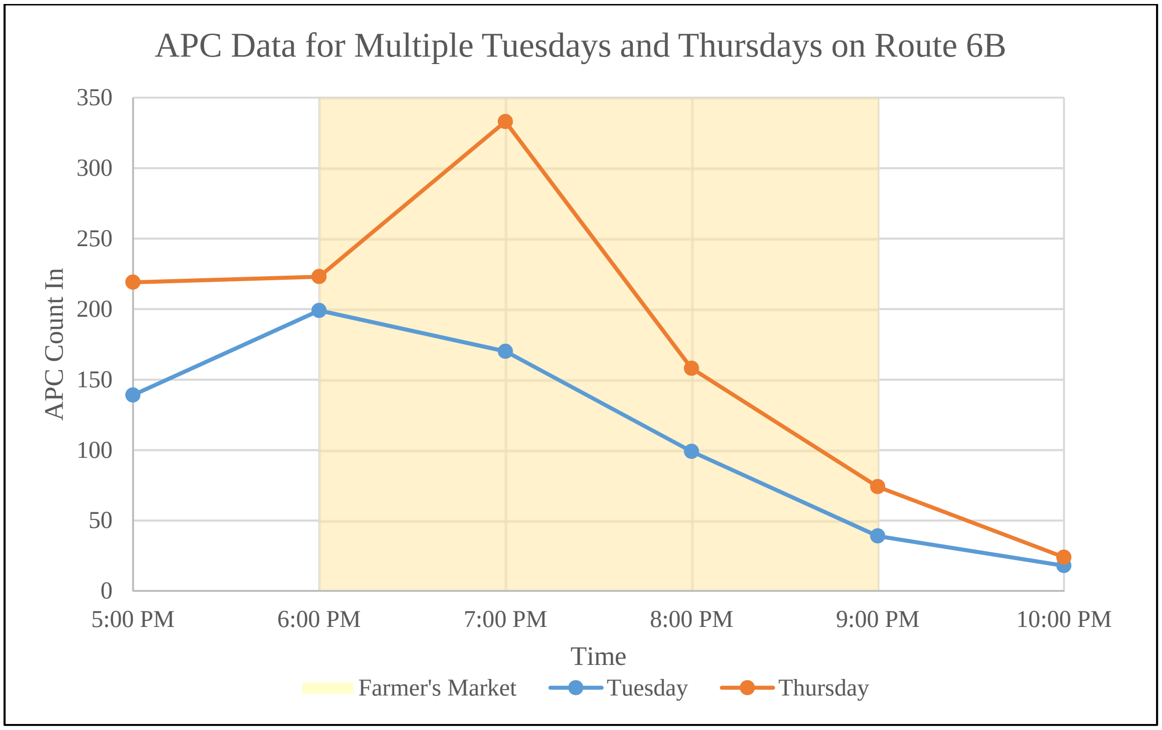


Figure 46: APC Data for Multiple Tuesdays and Thursdays on Route 6B

Figure 47 shows the combined passenger counts for Route 4. The data was used from three Tuesdays (March 14, April 25, and May 2, 2017) and three Thursdays (March 16, April 27, and May 4, 2017). The ridership from 6 PM to 8 PM is higher on Thursday than Tuesday from 6 PM to 8 PM, suggesting a higher ridership to serve students traveling from Cal Poly to Downtown for Farmer's Market. The gap in ridership between Tuesdays and Thursdays likely tapered off at 8 PM because students traveling back to Cal Poly from Downtown would have used Route 6B because Route 4 doesn't travel directly back to Cal Poly from Downtown. The combined ridership during the Tuesday from 5 PM to 10 PM of 685 passengers saw a 26% increase to 863 passengers during the same

hours on Thursday PM hours. Combining the passenger counts from Route 4 and 6B, the ridership saw a 40% increase from Tuesday PM hours to the Thursday PM hours.

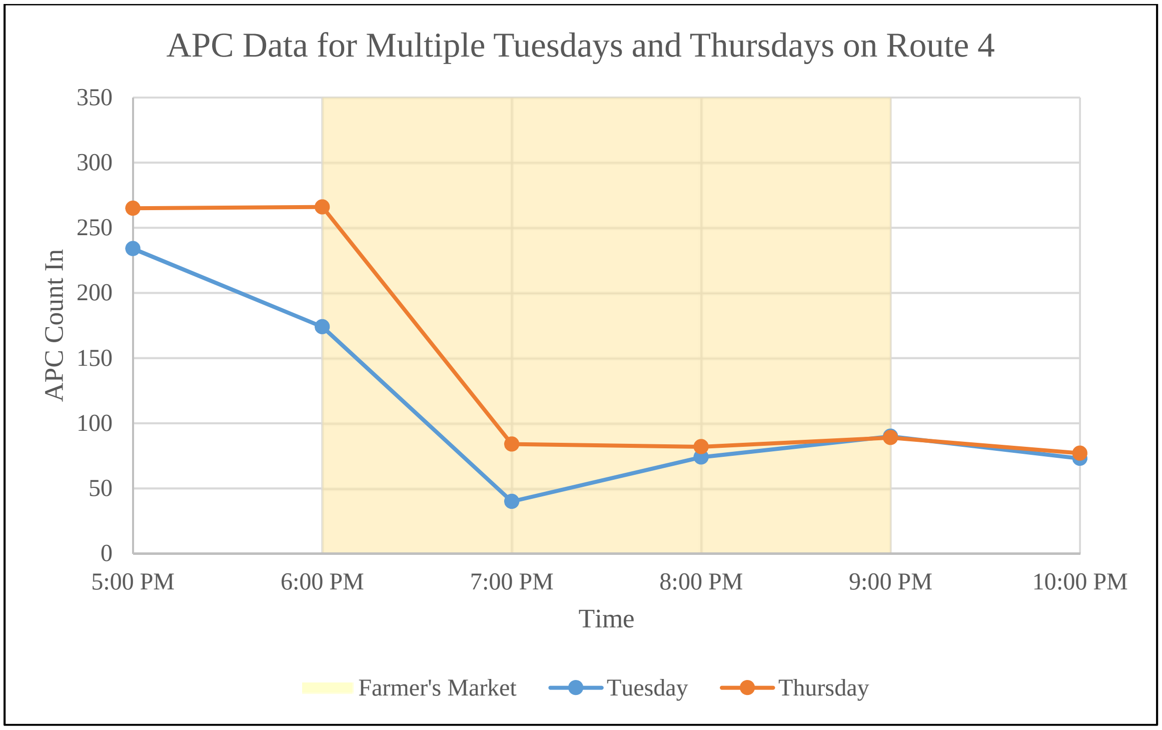


Figure 47: APC Data for Multiple Tuesdays and Thursdays on Route 4

Based on the observed increase in transit ridership during Farmer’s Market times, it is reasonable to invest time and resources into studying the inference that special events such as the Downtown San Luis Obispo Farmer’s Market attract higher ridership.

4.2 Data Processing and Reduction

The Bluetooth data collected with the BlueMAC detectors contains a significant amount of noise and inconsistencies that must be filtered out. For example, at a bus stop, non-passengers near the bus may be detected. At a traffic signal, a driver’s device in his or her vehicle near the bus may be detected. Some passengers may disable their Bluetooth during a trip.

4.2.1 Multi-Step Filter System for Processing Data

Several data filtering methods were identified in the literature review that provided a foundation for the data filter system used. The filters from the literature review that were used for this case study's data filtering process include the filter that eliminates infrequently detected devices and the filter that eliminates devices beyond a designated trip duration threshold (Dunlap et al., 2016). The main goal of filtering the data was to eliminate the inconsistencies and retain the detections from onboard Bluetooth devices. Statistical analysis software (SAS) cleaned the data through a multi-step filter. The SAS code for the data filtering is located in Appendix B: Sample Code.

In filter 1, the detection was deleted if the MAC address was not six units. This filter eliminates devices that are not handheld Bluetooth devices and retains detections of potential passenger trips. Detections were retained only if the MAC address contained six units of numbers and letters.

In filter 2, the data was filtered to include the hours the bus served on the certain day and route. For example, service hours for Route 6B are from 7 AM to 9 PM, so the data beyond the service time frame was filtered out. The log in and log out times were obtained from the SLO Transit daily dispatch logs.

In filter 3, the MAC address and observations were eliminated if the number (N) of observations was less than six. This means that six detections do not represent six consecutive seconds, but could be detections that occurred over a span of seconds or in the same second. This value is moderately conservative but not restrictive that potential valid observations are eliminated.

In filter 4, the MAC addresses were sorted into separate trips if they were detected at different times of the day. For example, if a MAC address was detected at 9 AM and then again at 12 PM, the detection times were split into two separate trips, assuming that these are separate bus trips to get from home to a destination, then from the destination to home or elsewhere.

In filter 5, detection was deleted if the cumulative time elapsed was less than three minutes or greater than the route duration. Based on the SLO Transit schedule, the running time between any two bus stops is always above three minutes. Based on the route, the maximum trip time is less than the time it takes for a bus to make a complete loop of its route. The ride duration from the data must adhere to the time constraints. The trip duration parameters were based on historical SLO Transit operating records and the bus schedules. This filter removes detections with unreasonably short or long detection durations. The ride durations of the remaining detections were calculated as the time difference between the initial time detected and final time detected for a given ride. The data filtering flowchart is summarized in Figure 48. The number of detections remaining after each filter applied is shown in Table 7.

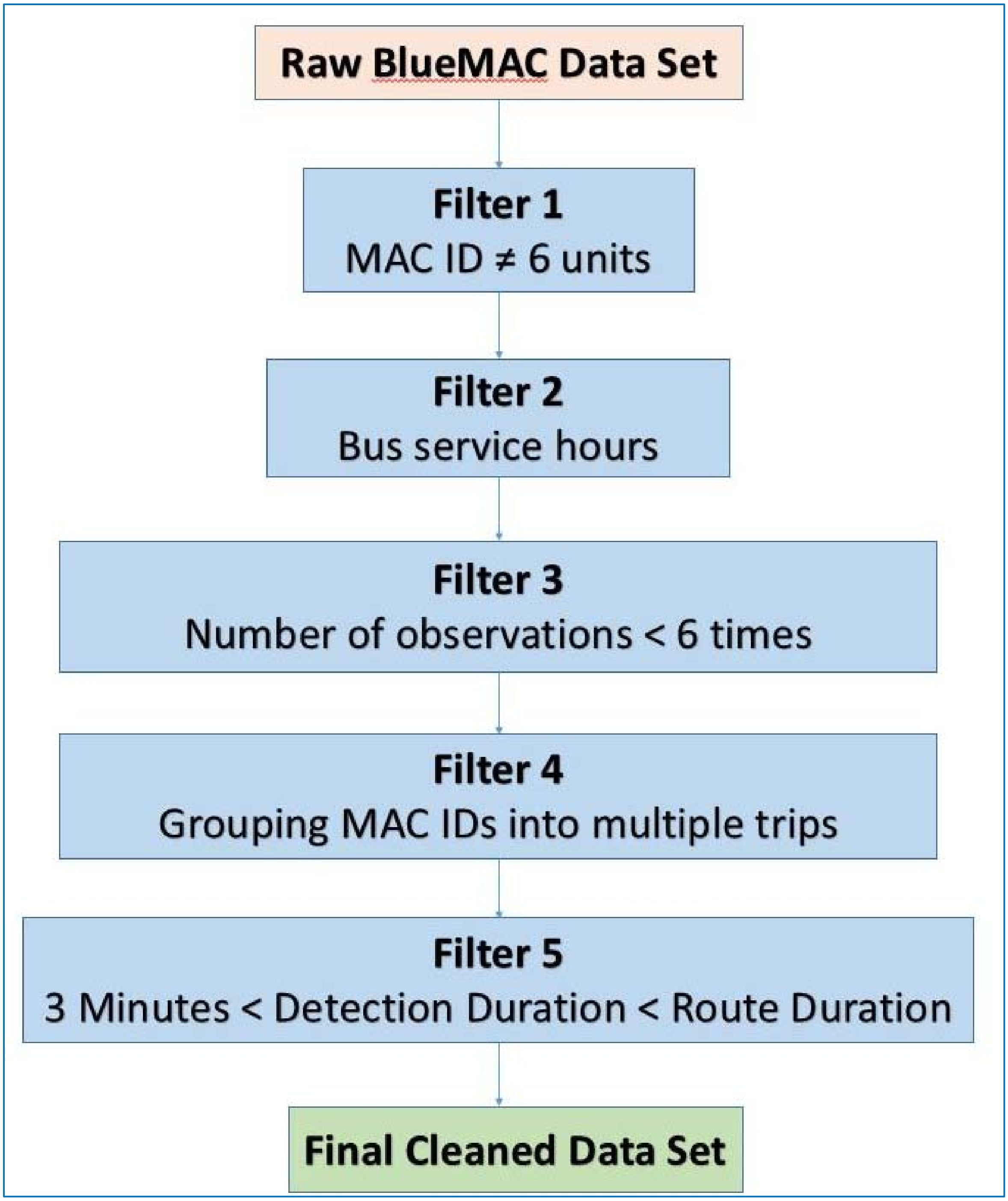


Figure 48: Filtering Method for Raw BlueMAC Data

Table 7: Remaining Bluetooth Detections After Application of Each Filter

Week	Route	Number of Bluetooth Detections Remaining After Successive Application of Each Filter					
		Raw Data	**Filter 1**	**Filter 2**	**Filter 3**	**Filter 4**	**Filter 5**
1	2	2,103,718	2,049,760	1,053,340	1,047,096	8,247	1,179
	4A	1,062,926	1,037,735	771,780	768,725	3,797	156
	5A	1,779,673	1,771,123	1,541,686	1,533,089	10,476	523
	6B	8,682,878	8,340,621	7,511,983	7,504,733	14,105	2,019
2	2	775,067	759,136	625,723	620,938	5,023	952
	3	68,504	66,425	44,079	1,694,541	2,854	581
	5A	3,047,676	2,947,429	2,586,649	6,644,768	12,704	700
	6B	5,665,591	5,442,883	4,275,227	4,268,249	10,473	1,607
3	2	2,726,915	2,618,106	1,465,272	1,457,148	8,783	989
	4B	1,826,970	1,772,830	1,703,365	1,694,541	11,011	442
	6A	9,229,445	8,899,156	6,651,499	6,644,768	9,539	1,676
4	4A	1,244,572	1,188,218	972,219	967,548	5,148	235
	5B	1,964,558	1,964,558	1,712,506	1,705,032	11,864	452
5	5A	1,241,734	1,198,491	883,575	879,026	9,577	337
	6A	3,230,352	3,185,587	1,477,791	1,475,891	4,035	413

4.2.2 BlueMAC Raw Data and Filtered Data Comparison

Figures 49 through 52 illustrate the total number of devices detected based on the raw Bluetooth data versus the filtered Bluetooth data.

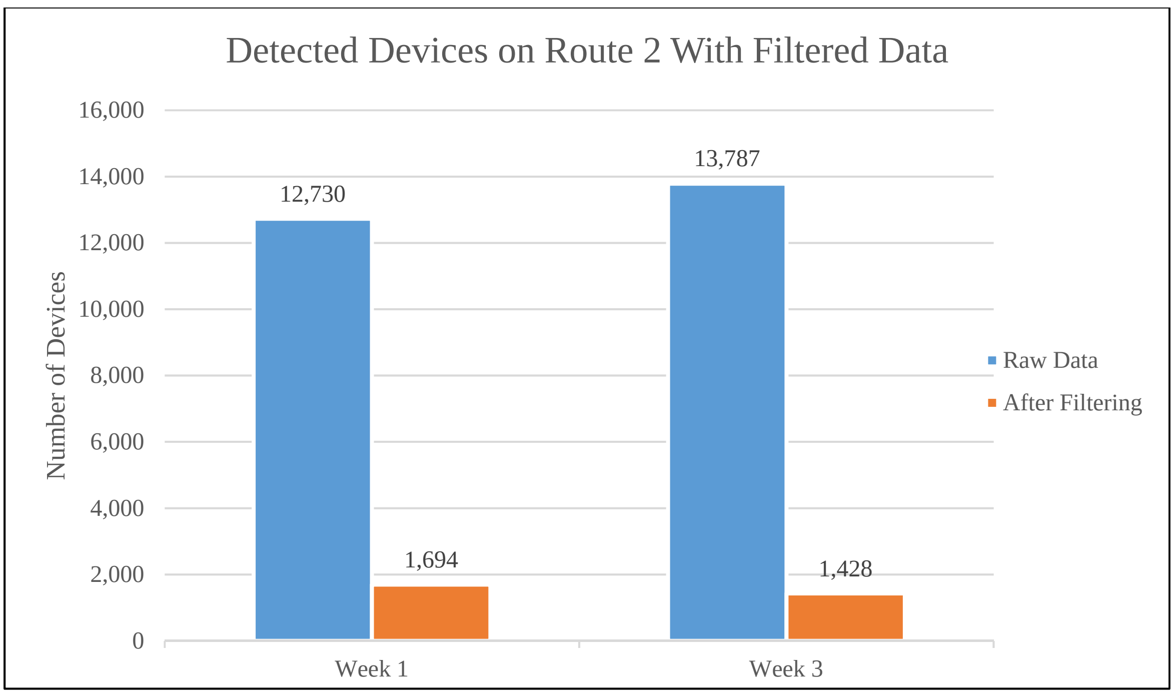


Figure 49: Weekly Detections on Route 2 Comparing Raw Data and Filtered Data

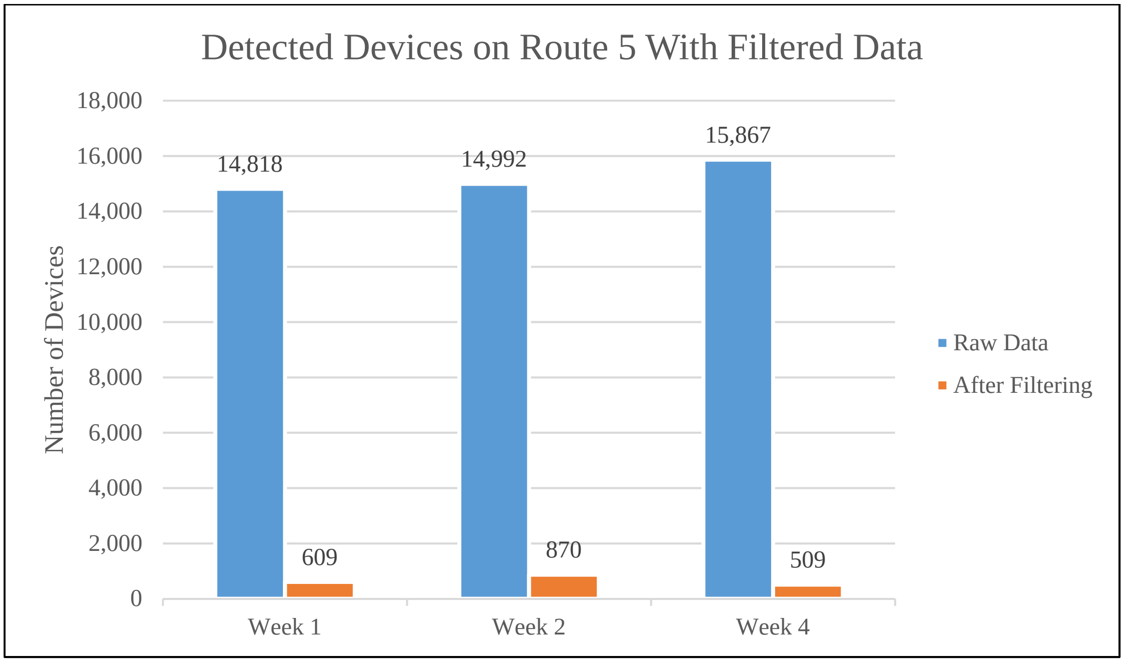


Figure 50: Weekly Detections on Route 5 Comparing Raw Data and Filtered Data

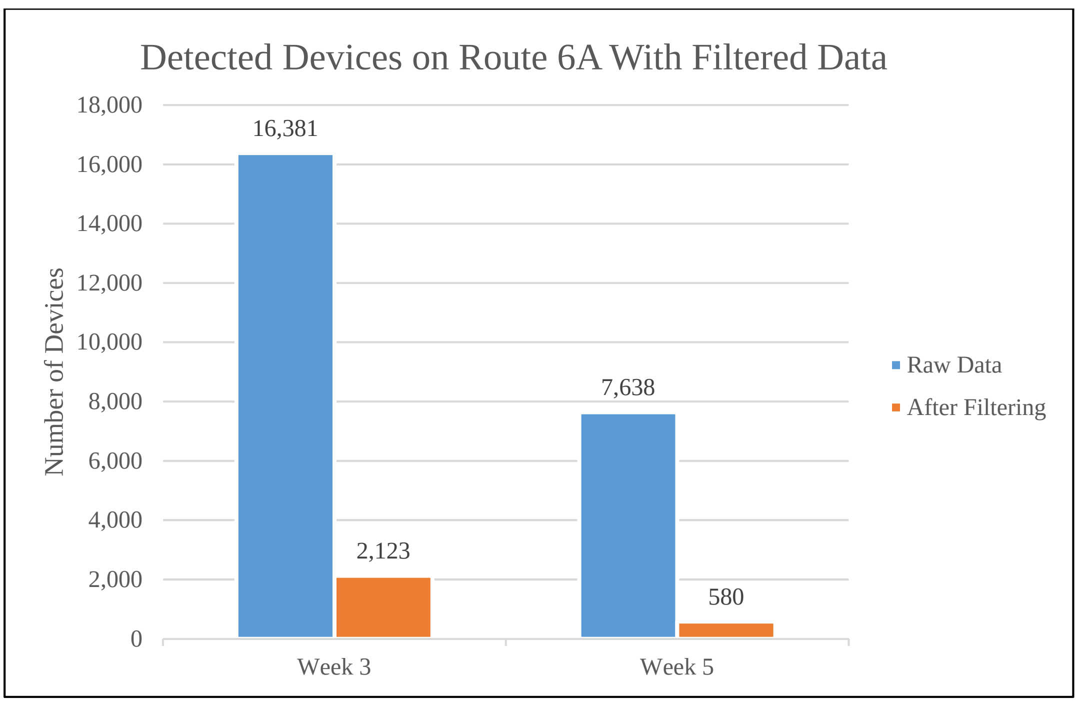


Figure 51: Weekly Detections on Route 6A Comparing Raw Data and Filtered Data

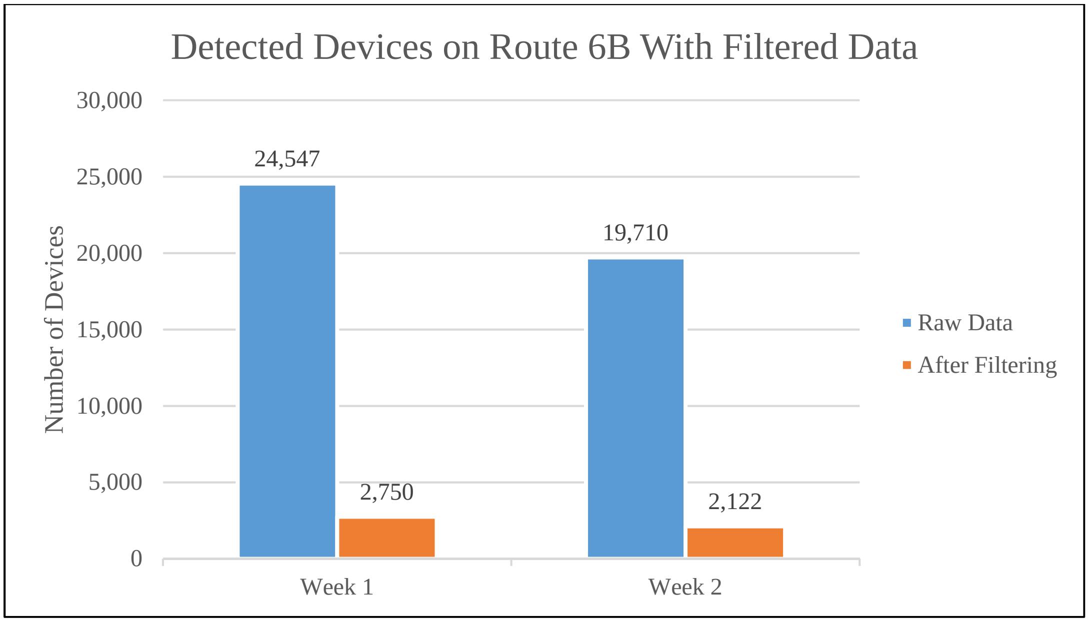


Figure 52: Weekly Detections on Route 6B Comparing Raw Data and Filtered Data

Route 2 in Figure 49 saw an average 88.17% decrease from the raw data to the filtered data. Route 5 in Figure 50 had an average 95.63% reduction. Route 6A in Figure 51 saw an average 89.72% decrease, and Route 6B in Figure 52 saw an average 89.02% reduction. These figures indicate that a large number of detected devices were detected once or for a short period of time of a few seconds. These extraneous devices were likely other road users within the sensor's radius.

4.2.3 Filtered BlueMAC Data and Automated Passenger Counter Comparison

The filters were applied to the BlueMAC data to extract counts of unique passenger information and to compare the filtered data to the ground-truth APC data. The filtered BlueMAC data was binned into hourly counts, then graphed with the APC count in data. The data was processed through all of the five filters listed in Figure 48. Figures 53 to 55 show the graphs for Route 2.

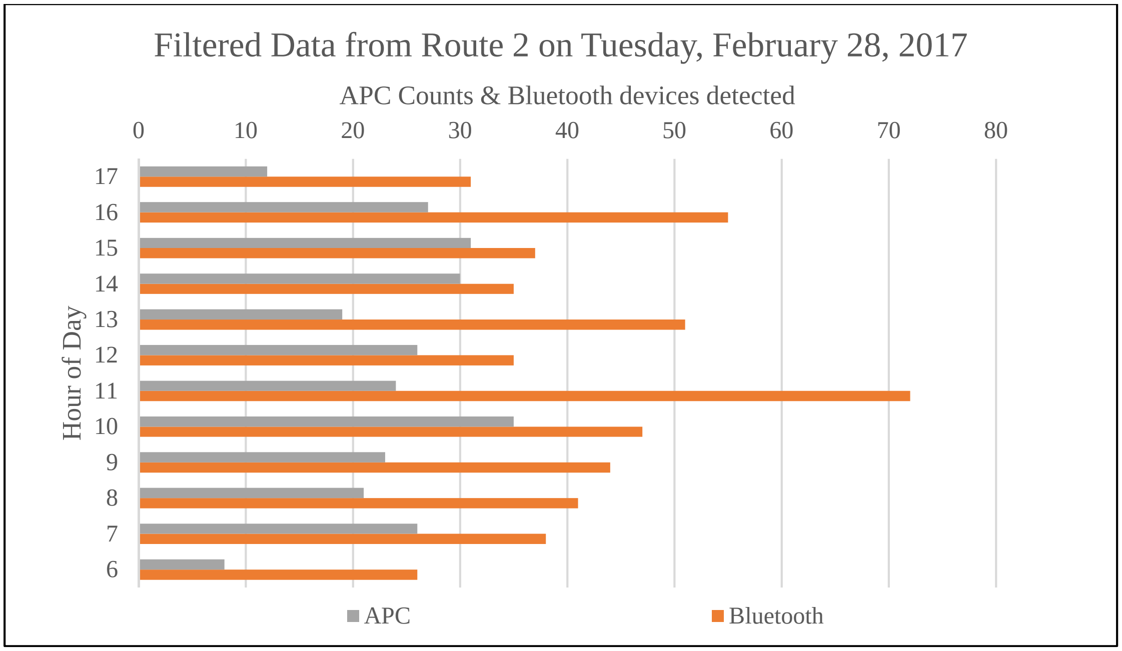


Figure 53: APC Counts and Filtered Bluetooth Devices on Route 2 on February 28

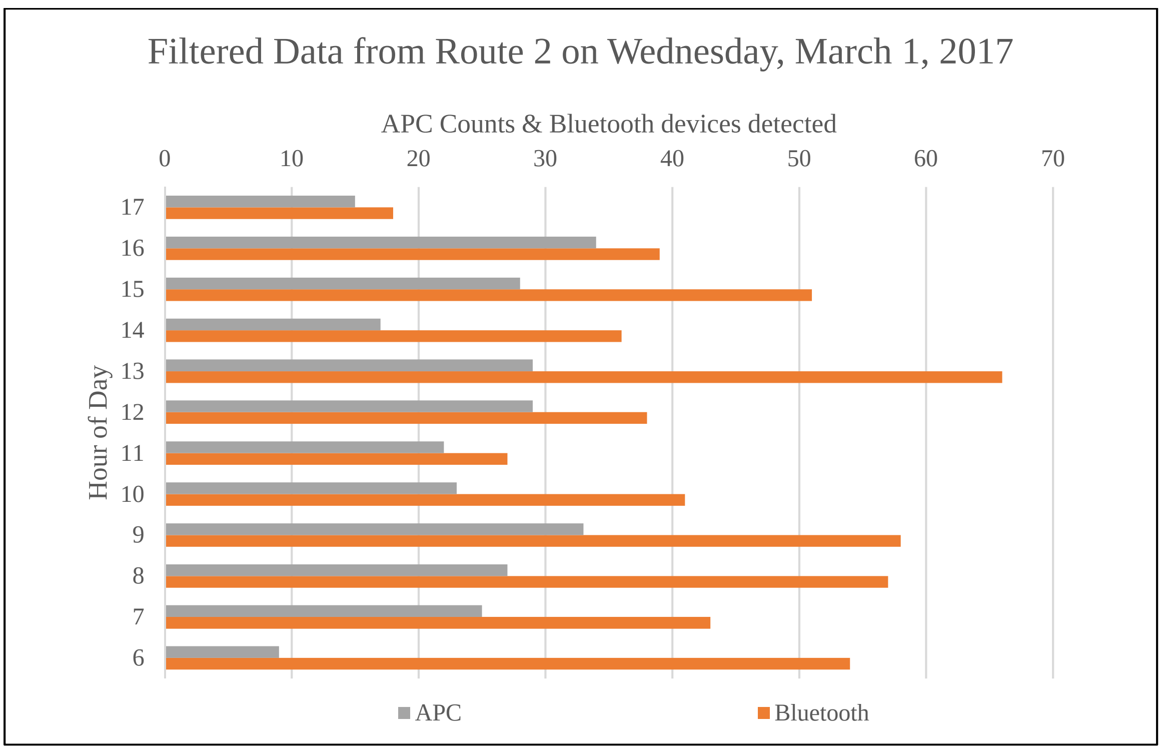


Figure 54: APC Count In and Filtered Bluetooth Devices on Route 2 on March 1

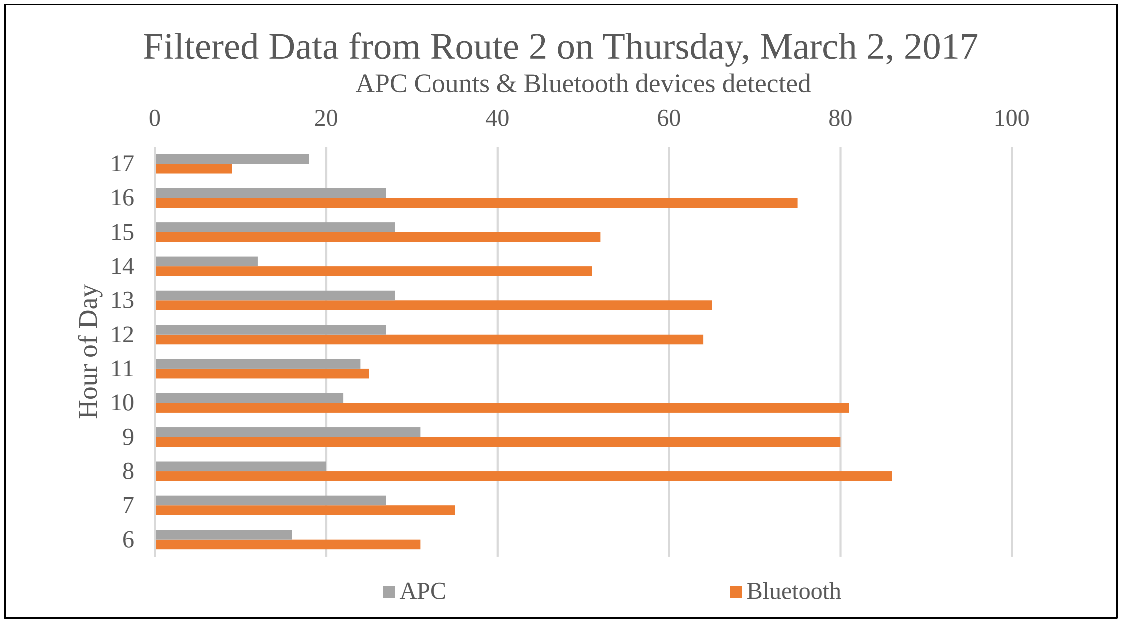
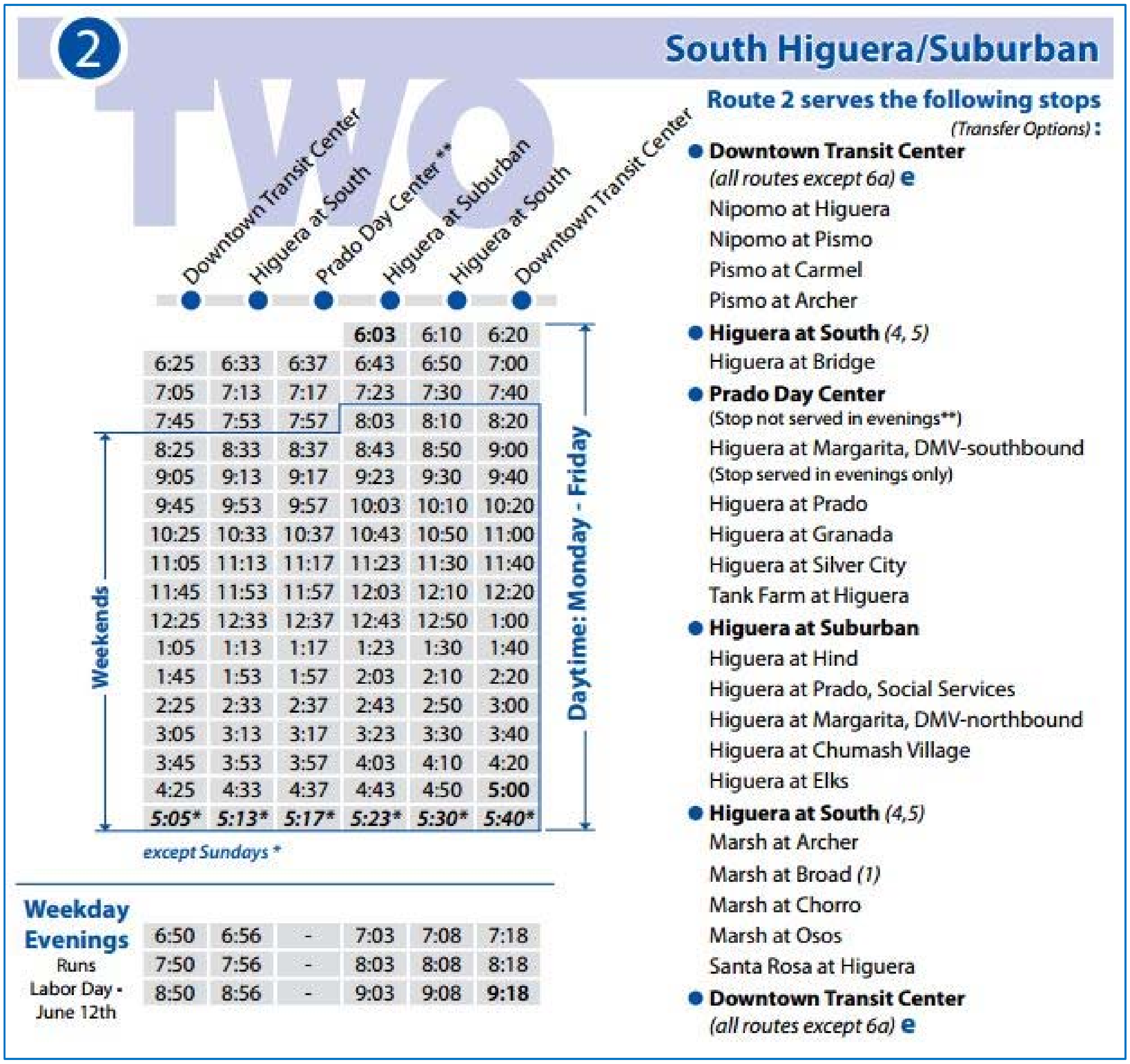


Figure 55: APC Count In and Filtered Bluetooth Devices on Route 2 on March 2

The filtered BlueMAC data was binned into hourly counts, then graphed with the APC count in data. After the filtering process, Route 2 had more devices detected per hour compared to the APC counts. Based on the literature review and passenger surveys, it was expected that there would be significantly less Bluetooth devices detected than the number of passengers counted by APC. The filter with the duration time could have contributed to the higher counts of Bluetooth devices since the maximum detection time was 40 minutes. It takes 35 minutes for a bus on Route 2 to make a complete loop based on the schedule shown in Figure 56.



2 South Higuera/Suburban

TWO

Downtown Transit Center	Higuera at South	Prado Day Center **	Higuera at Suburban	Higuera at South	Downtown Transit Center
			6:03	6:10	6:20
6:25	6:33	6:37	6:43	6:50	7:00
7:05	7:13	7:17	7:23	7:30	7:40
7:45	7:53	7:57	8:03	8:10	8:20
8:25	8:33	8:37	8:43	8:50	9:00
9:05	9:13	9:17	9:23	9:30	9:40
9:45	9:53	9:57	10:03	10:10	10:20
10:25	10:33	10:37	10:43	10:50	11:00
11:05	11:13	11:17	11:23	11:30	11:40
11:45	11:53	11:57	12:03	12:10	12:20
12:25	12:33	12:37	12:43	12:50	1:00
1:05	1:13	1:17	1:23	1:30	1:40
1:45	1:53	1:57	2:03	2:10	2:20
2:25	2:33	2:37	2:43	2:50	3:00
3:05	3:13	3:17	3:23	3:30	3:40
3:45	3:53	3:57	4:03	4:10	4:20
4:25	4:33	4:37	4:43	4:50	**5:00**
*5:05**	*5:13**	*5:17**	*5:23**	*5:30**	*5:40**

Weekends — Daytime: Monday - Friday

*except Sundays **

Weekday Evenings Runs Labor Day - June 12th					
6:50	6:56	-	7:03	7:08	7:18
7:50	7:56	-	8:03	8:08	8:18
8:50	8:56	-	9:03	9:08	**9:18**

Route 2 serves the following stops
(Transfer Options):

- **Downtown Transit Center** *(all routes except 6a)* e
- Nipomo at Higuera
- Nipomo at Pismo
- Pismo at Carmel
- Pismo at Archer
- **Higuera at South** *(4, 5)*
- Higuera at Bridge
- **Prado Day Center** (Stop not served in evenings**)
- Higuera at Margarita, DMV-southbound (Stop served in evenings only)
- Higuera at Prado
- Higuera at Granada
- Higuera at Silver City
- Tank Farm at Higuera
- **Higuera at Suburban**
- Higuera at Hind
- Higuera at Prado, Social Services
- Higuera at Margarita, DMV-northbound
- Higuera at Chumash Village
- Higuera at Elks
- **Higuera at South** *(4,5)*
- Marsh at Archer
- Marsh at Broad *(1)*
- Marsh at Chorro
- Marsh at Osos
- Santa Rosa at Higuera
- **Downtown Transit Center** *(all routes except 6a)* e

Figure 56: SLO Transit Route 2 Schedule

Assuming that passenger trips do not last the entire 35 minutes, the SAS data filtering for trip duration was adjusted for different trip times, as shown in Figure 57. The filters were adjusted for maximum trip times of 15 minutes, 20 minutes, 25 minutes, and 30 minutes. Except for 6 AM and 5 PM, APC counts were higher than all the trip durations as expected. Shown in Figure 57, different trip durations adjusted the Bluetooth detection counts. When the trip duration was 30 minutes or less, the Bluetooth counts were less than the APC counts. The filter for 20-minute maximum trip durations counted more devices than 15 minutes, 25 minutes, and 30 minutes.

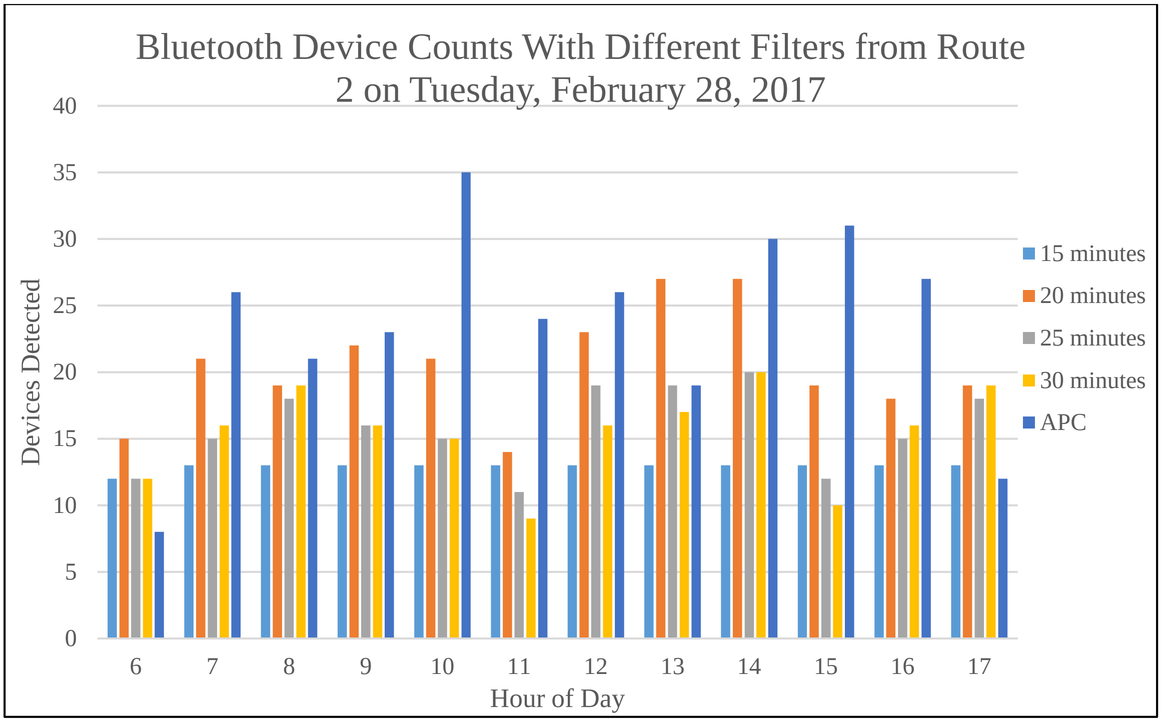


Figure 57: Bluetooth Counts with Different Filters on Route 2 on February 28

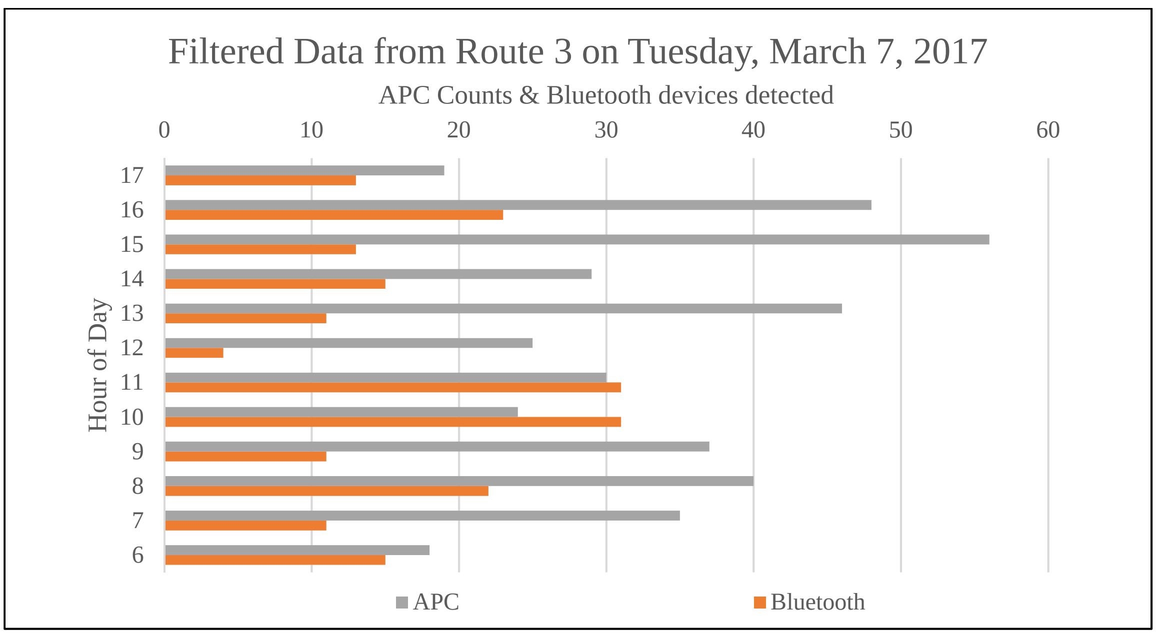


Figure 58: APC Count In and Filtered Bluetooth Devices on Route 3 on March 7

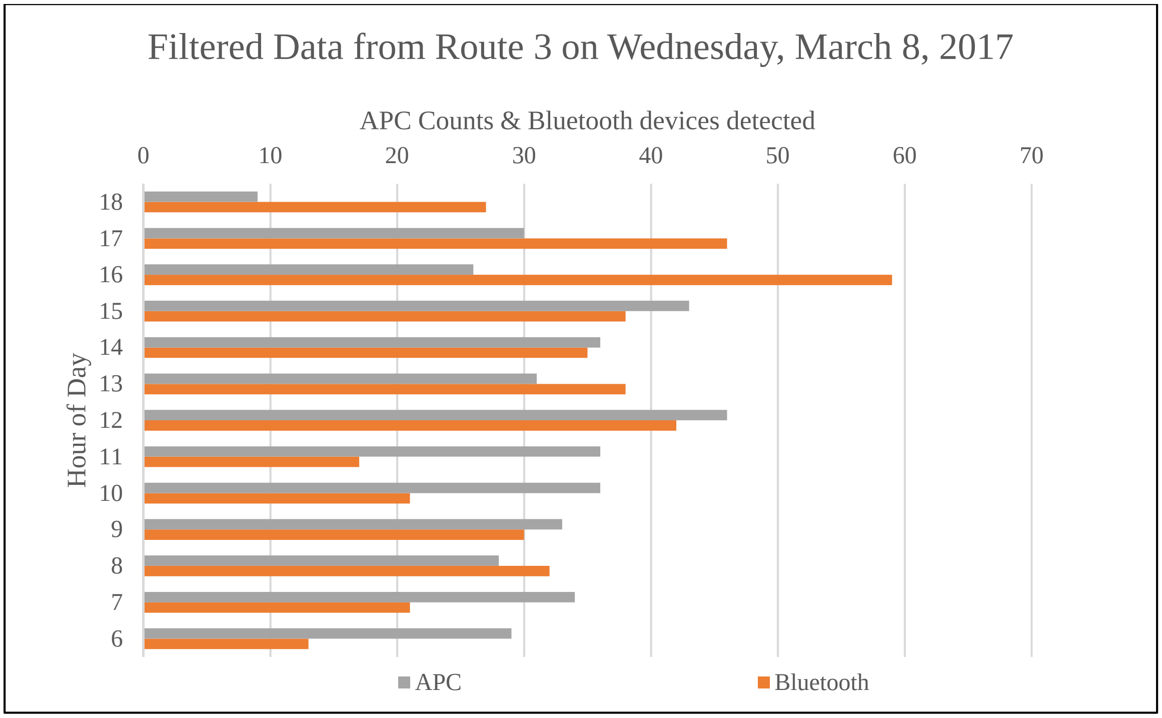


Figure 59: APC Count In and Filtered Bluetooth Devices on Route 3 on March 8

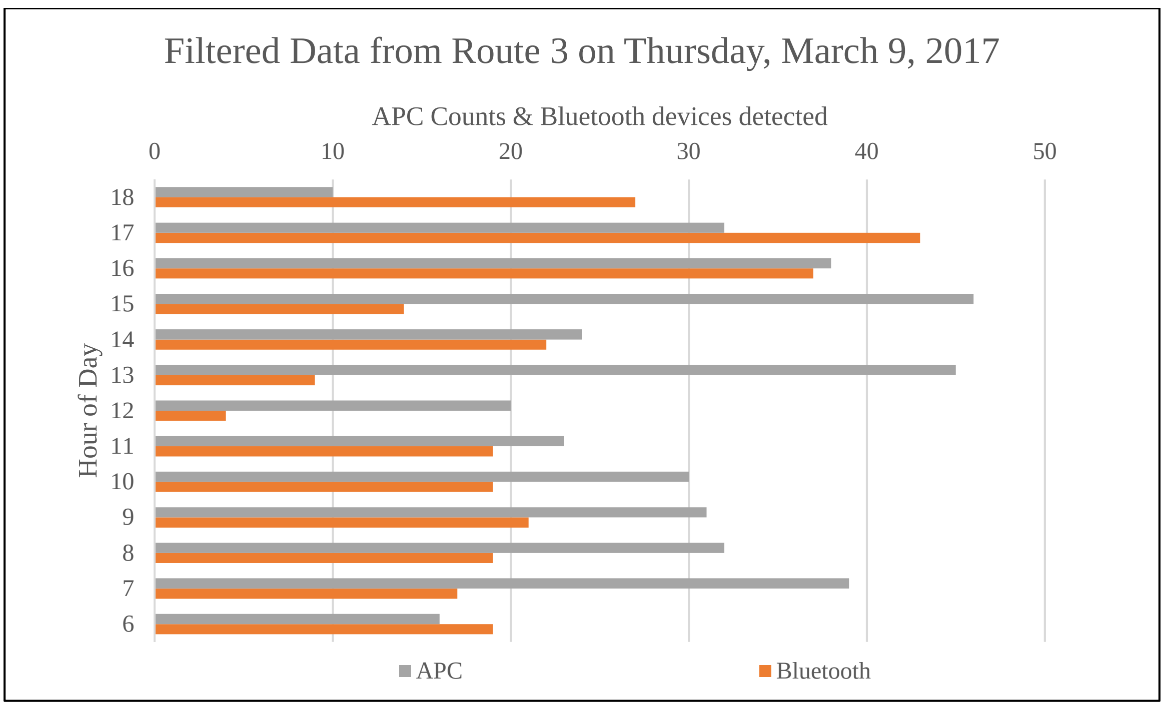


Figure 60: APC Count In and Filtered Bluetooth Devices on Route 3 on March 9

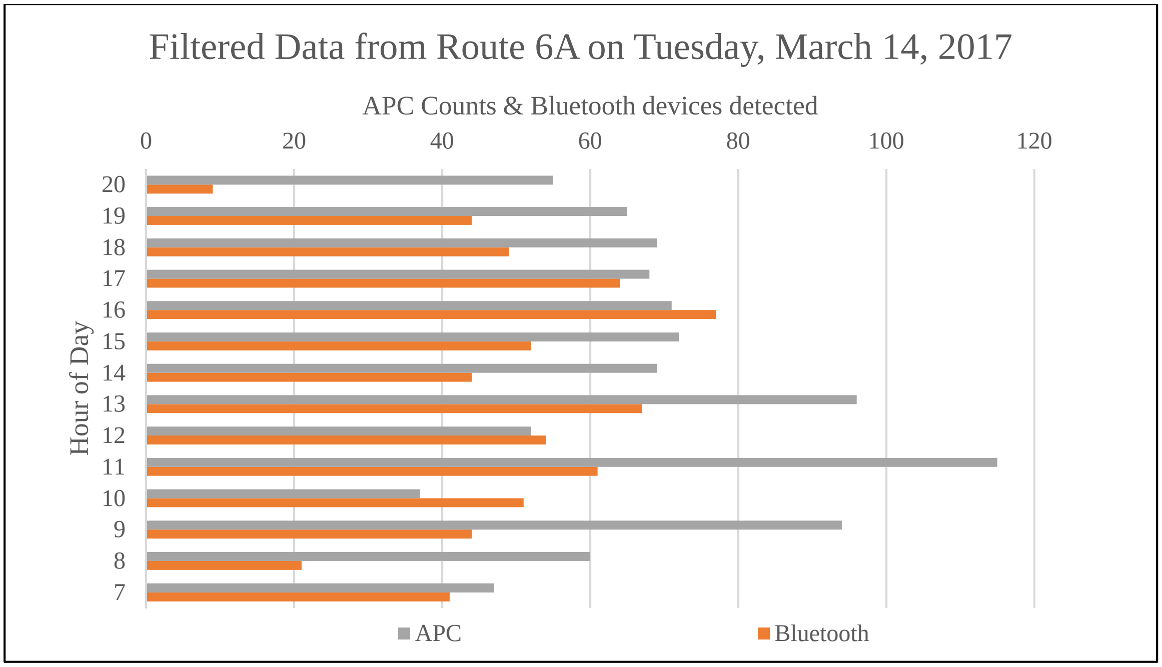


Figure 61: APC Count In and Filtered Bluetooth Devices on Route 6A on March 14

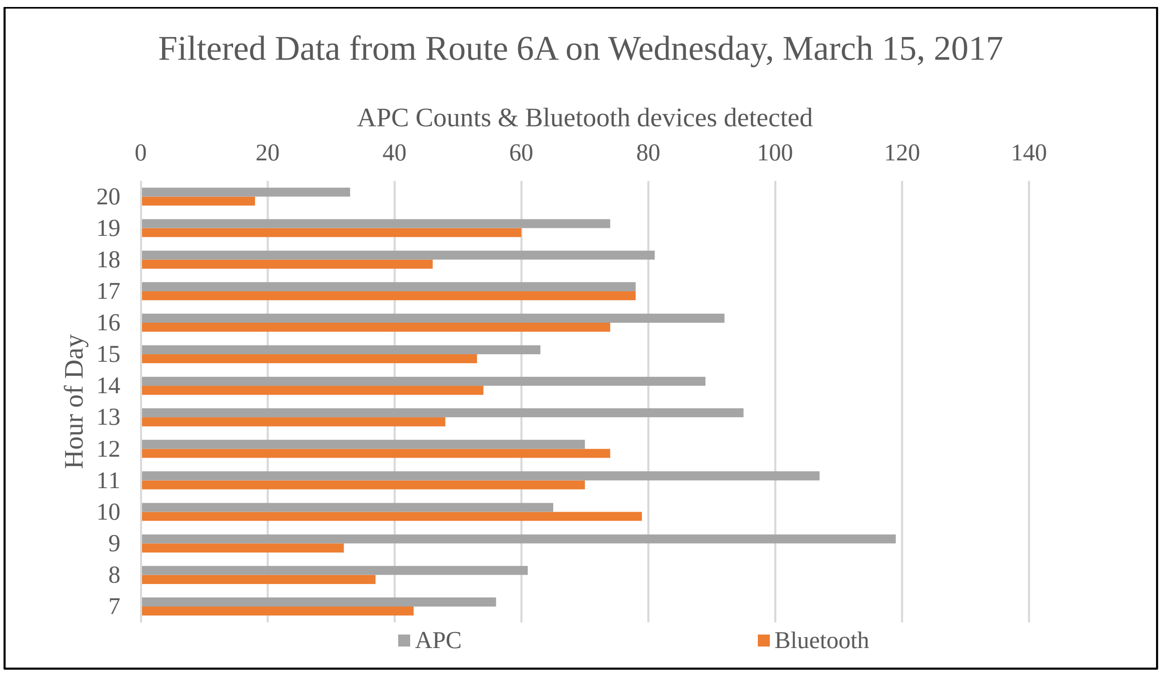


Figure 62: APC Count In and Filtered Bluetooth Devices on Route 6A on March 15

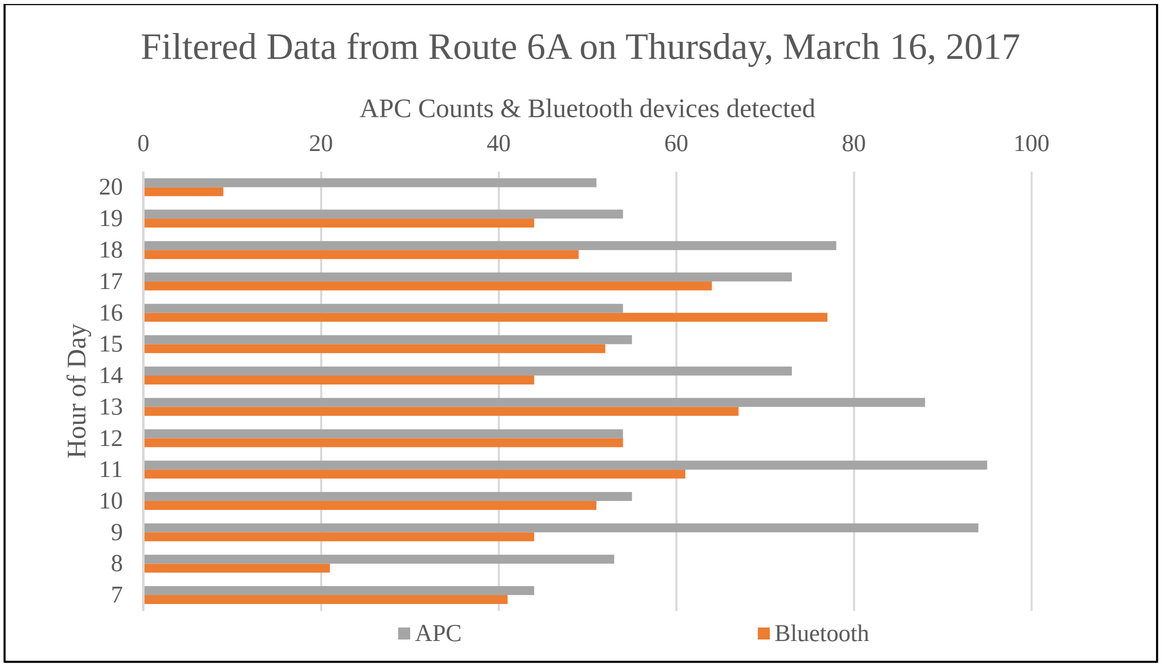


Figure 63: APC Count In and Filtered Bluetooth Devices on Route 6A on March 16

In Figure 63, the BlueMAC trends generally follow the APC patterns – the counts increase and decrease similarly for Route 6A. The APC and Bluetooth data were closest on noon on Tuesday, Wednesday, and Thursday of the week.

Table 8: Summary of Filtered BlueMAC Data and APC Data for Routes 2, 3, and 6A

Day	Date	Route	Bluetooth Raw Detection	Bluetooth Filtered Detection	APC	R^2	Percent Difference
Tuesday	2/28/2017	2	4,244	512	282	0.1062	-81.56%
Wednesday	3/1/2017	2	4,169	528	291	0.1231	-81.44%
Thursday	3/2/2017	2	4,317	654	280	0.1274	-133.57%
Tuesday	3/7/2017	3	1,481	200	407	0.0019	50.86%
Wednesday	3/8/2017	3	1,580	419	417	0.0023	-0.48%
Thursday	3/9/2017	3	1,551	270	386	0.0031	30.05%
Tuesday	3/14/2017	6A	5,521	678	970	0.1481	30.10%
Wednesday	3/15/2017	6A	5,577	766	1,083	0.0649	29.27%
Thursday	3/16/2017	6A	5,283	678	921	0.1283	26.38%
			Average Percent Difference				-14.49%

Table 8 above shows the weekly Bluetooth and APC counts for Routes 2, 3, and 6A. The average percent difference between the weekly APC counts and the filtered

Bluetooth detections is -14.49%. The APC data provides the ground truth against the performance of the BlueMAC data accuracy in passenger detection. Route 6A was chosen for the origin-destination matrix generation because of the consistent percent differences, predictable ridership, and its high ridership numbers.

4.2.4 Farmer's Market Analysis Using BlueMAC Data

The Bluetooth data on Thursday PM hours was not analyzed for Farmer's Market times because the SAS data filtering eliminated the BlueMAC during PM hours. The filter was applied to retain the time frames based on the log-in and log-out times of the buses per day. The times were obtained from the SLO Transit Daily Dispatch Logs. APC data was used to create OD matrices during the Thursday PM hours, as described in 4.3 Origin-Destination Estimation.

4.3 Origin-Destination Estimation

After the filters were applied and the final cleaned data were obtained, the origin and destination information was represented in the form of OD matrices. Before creating the OD matrix for Bluetooth data, OD matrices were created using APC data and a data collection from a passenger count on the bus.

4.3.1 OD Estimation for Route 6A Using APC Data and Bluetooth Data

The APC data was used as the reliable "ground-truth" against the BlueMAC data based on a trial run as a passenger on the SLO Transit buses. At each bus stop, the number of boarding and alighting passengers were counted and recorded. The counts were compared to the APC data for the same time and date, and the counts matched. Route 6A was represented in the OD matrices. Figure 64 below shows Route 6A and the

stops along the route. Route 6A runs in a counter-clockwise loop connected Cal Poly to the residential neighborhoods west of the campus.

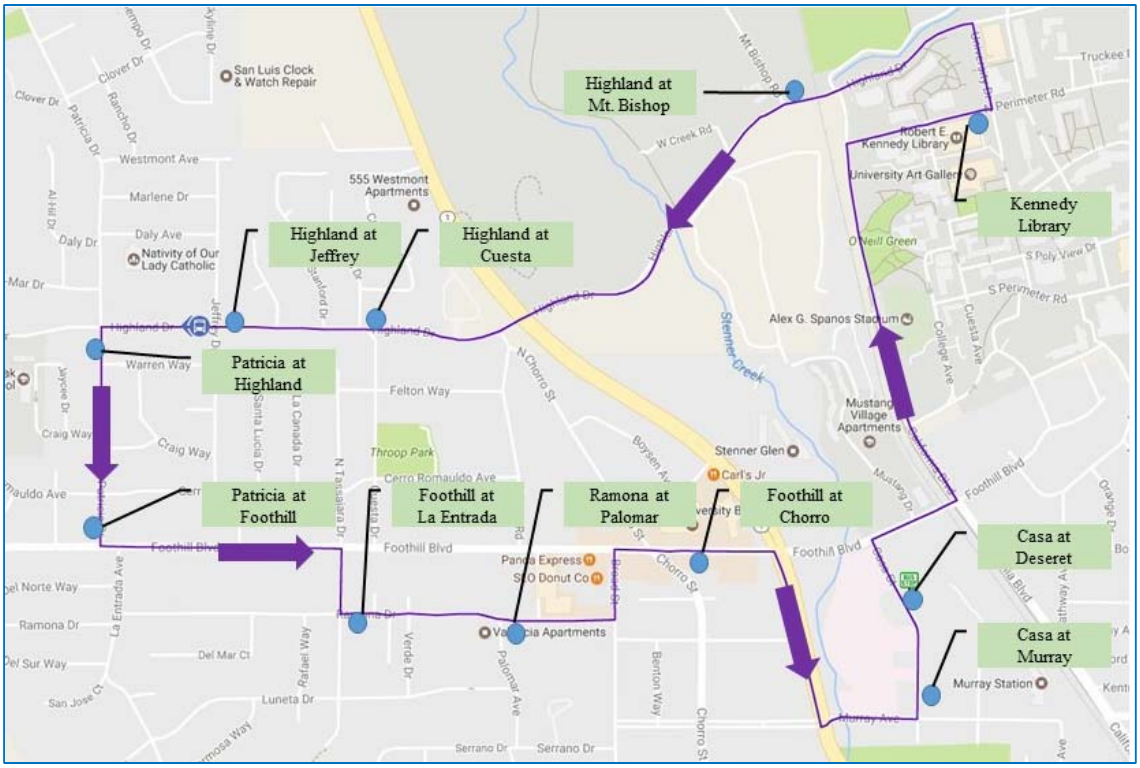
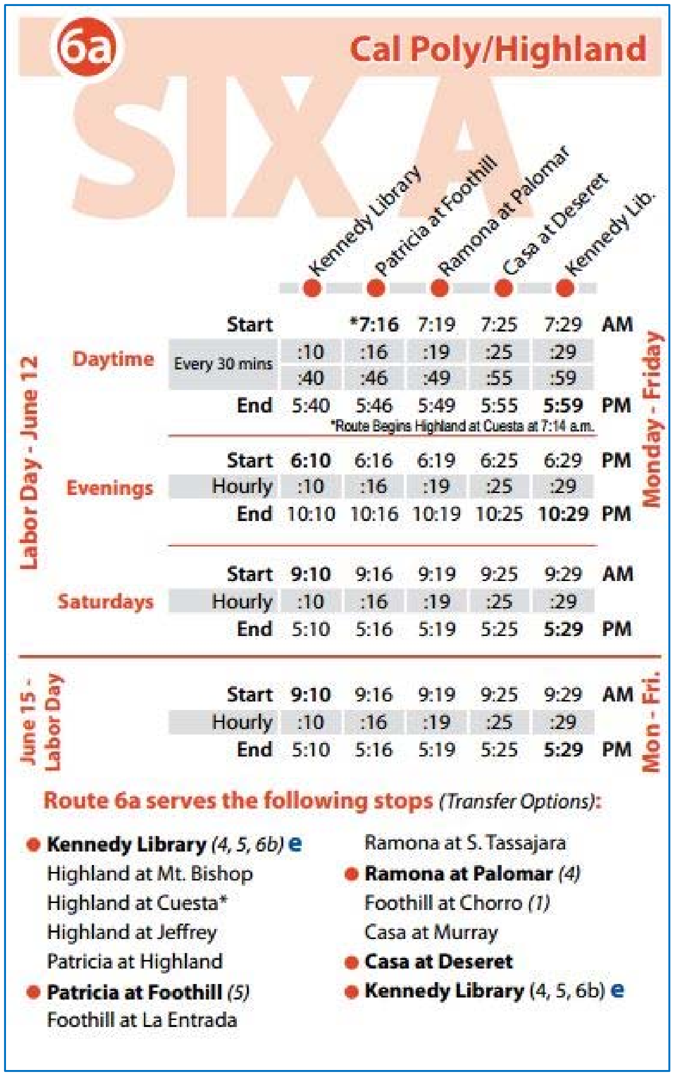


Figure 64: SLO Transit Route 6A Bus Stops

For daytime schedules, one complete loop of Route 6A begins ten minutes after the hour and ends 30 minutes after the hour at the Kennedy Library bus stop. The loop begins again 40 minutes after the hour and completes on the hour. The complete schedule of Route 6A is shown in Figure 65.


6a Cal Poly/Highland

SIX A

		Kennedy Library	Patricia at Foothill	Ramona at Palomar	Casa at Deseret	Kennedy Lib.	
Labor Day - June 12, Daytime (Monday - Friday)	Start		*7:16	7:19	7:25	7:29	AM
	Every 30 mins	:10	:16	:19	:25	:29	
		:40	:46	:49	:55	:59	
	End	5:40	5:46	5:49	5:55	5:59	PM
*Route Begins Highland at Cuesta at 7:14 a.m.							
Evenings	Start	6:10	6:16	6:19	6:25	6:29	PM
	Hourly	:10	:16	:19	:25	:29	
	End	10:10	10:16	10:19	10:25	10:29	PM
Saturdays	Start	9:10	9:16	9:19	9:25	9:29	AM
	Hourly	:10	:16	:19	:25	:29	
	End	5:10	5:16	5:19	5:25	5:29	PM
June 15 - Labor Day (Mon - Fri.)	Start	9:10	9:16	9:19	9:25	9:29	AM
	Hourly	:10	:16	:19	:25	:29	
	End	5:10	5:16	5:19	5:25	5:29	PM

Route 6a serves the following stops *(Transfer Options)*:

- **Kennedy Library** *(4, 5, 6b)* e
- Highland at Mt. Bishop
- Highland at Cuesta*
- Highland at Jeffrey
- Patricia at Highland
- **Patricia at Foothill** *(5)*
- Foothill at La Entrada
- Ramona at S. Tassajara
- **Ramona at Palomar** *(4)*
- Foothill at Chorro *(1)*
- Casa at Murray
- **Casa at Deseret**
- **Kennedy Library** (4, 5, 6b) e

Figure 65: SLO Transit Route 6A Bus Schedule

During the bus survey runs, two loops of the route were observed from 5:10 PM to 5:40 PM on March 16, 2017. One OD matrix was generated based on the APC data, and another based on the BlueMAC Data. Based on test rides on Route 6A, it was assumed that the Kennedy Library bus stop at Cal Poly was either the origin or destination of the trip. Due to the large image sizes, the matrices are in Appendix E: Origin-Destination Matrices.

A challenge of generating the OD matrices was the process of manually scrolling through both the APC and BlueMAC data to count the boardings and alightings at each

bus stop. In the passenger counting process, the APC data were counted at every bus stop. Each passenger boarding or alighting generates one line of data from the APC counter. Table 9 shows an example of the raw APC data.

Table 9: APC Bus Stop Events for Route 6A on March 16, 2017

RouteID	Route	StopID	StopName	Observed	CountIn	CountOut
957	Route 6A	63	Highland at Mt. Bishop	3/16/2017 9:06	0	1
957	Route 6A	63	Highland at Mt. Bishop	3/16/2017 9:06	0	1
957	Route 6A	63	Highland at Mt. Bishop	3/16/2017 9:06	1	0
957	Route 6A	63	Highland at Mt. Bishop	3/16/2017 9:06	1	0

After the passengers at each bus stop were counted, the numbers were inputted onto the blank OD matrix. Then, the BlueMAC data was used to generate the second OD matrix. The filtered BlueMAC data sets were used to manually count the passenger trips on Route 6A. Table 10 shows an example of the BlueMAC data set. "N" represents the number of detections per device.

Table 10: Filtered BlueMAC Detections for Route 6A on March 16, 2017

Duration	Start Time	End Time	MAC Address	N
11:20	16MAR17:05:39:20 PM	16MAR17:05:50:40 PM	8175C8	14,264
19:18	16MAR17:05:44:59 PM	16MAR17:06:04:17 PM	B05642	4,912
14:16	16MAR17:05:45:45 PM	16MAR17:06:00:01 PM	F0984F	30

The timestamps from the APC data sets were manually matched with the BlueMAC start times and end times to determine where each passenger boarded and alighted. For example, the first detection time of MAC address 8175C8 was 5:39 PM. Based on the APC data, the Route 6A bus was located at the Cal Poly Kennedy Library Bus Stop as shown by passenger counts boarding and alighting the bus. Then, it was inferred that the passenger boarded the bus at the Kennedy Library bus stop. To

determine the destination, the APC data was checked to determine where the bus was located at the last detection time of MAC address 8175C8. With the last detection time of 5:50 PM, it was inferred that the passenger exited the bus at the Ramona and South Tassajara bus stop because the APC data showed that a passenger exited the bus when it reached the bus stop at that time. Few detections exceeded the time to complete a loop of Route 6A, and were not counted in the OD matrix. Based on the OD matrices of the APC and BlueMAC data, the BlueMAC OD matrix captured 17.6% of the total ridership from the APC matrix.

4.3.2 OD Estimation Using APC Data: Farmer's Market Analysis

The APC data from SLO Transit was used to generate an OD matrix for Route 6B during Farmer's Market times. Route 6B and its bus stops are shown below in Figure 66. Figure 67 shows the bus schedule for Route 6B. The bus completes one loop every thirty minutes, connecting Cal Poly to Downtown Transit Center and the surrounding residential area. A portion of the route runs the same route for the return and destination trip – bus stops Mill at Pepper to Downtown Transit Center are repeated for loop. Bluetooth data was not used due to the time-consuming process of counting passengers from the data, and the PM times that were necessary for the analysis were filtered out based on the bus service hours provided in the Daily Dispatch Logs.

OD matrices were generated for 5 PM to 11 PM on Tuesday, March 14, 2017 and Thursday, March 16, 2017. The OD matrices are in Appendix E: Origin-Destination Matrices. The matrices show a higher ridership on Thursday nights compared to the Tuesday nights. This increased ridership derives from the trip demand connecting Cal Poly to Downtown San Luis Obispo for the weekly Farmer's Market. The Kennedy

Library bus stop and Performing Arts Center bus stop were combined into one origin or destination and labeled “Cal Poly” on the origin-destination matrix.

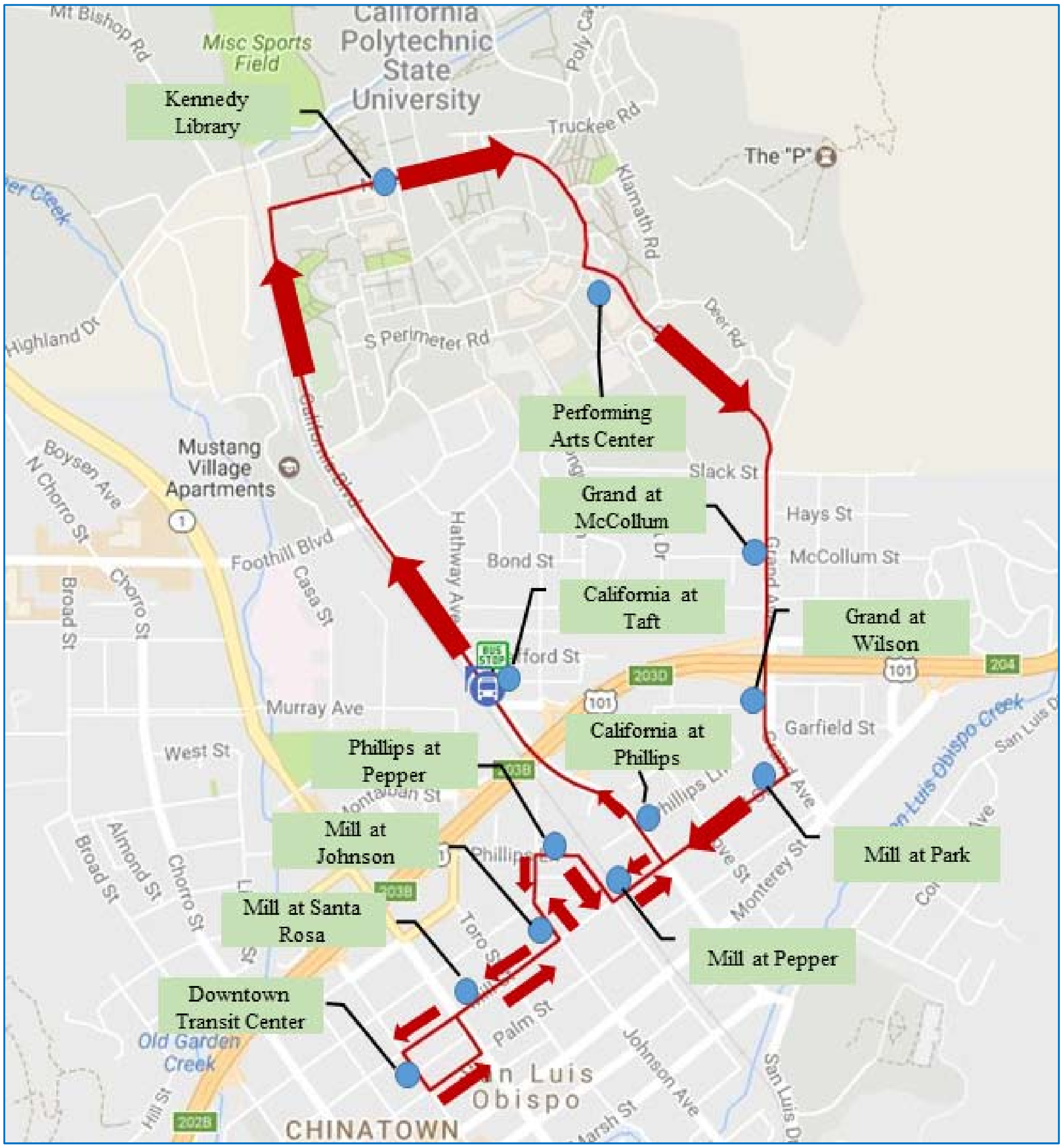
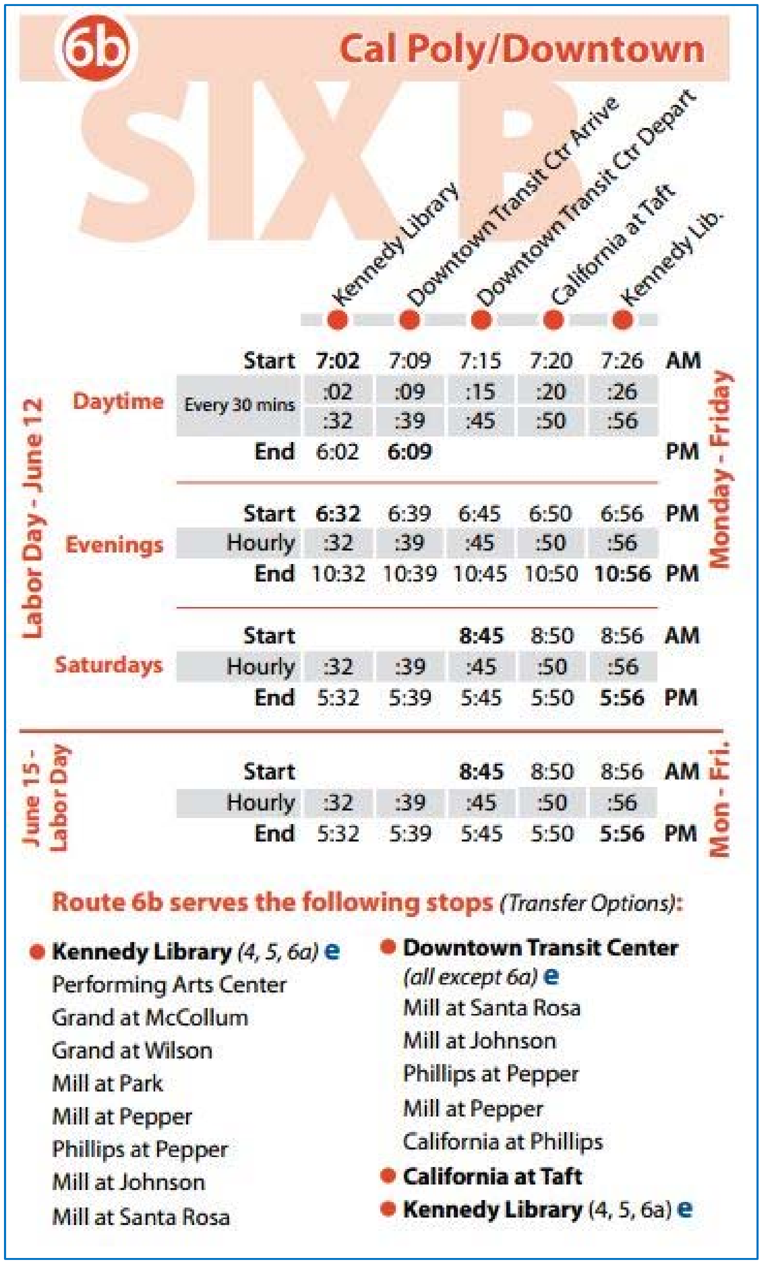


Figure 66: SLO Transit Route 6B Bus Stops



6b Cal Poly/Downtown

SIX B

			Kennedy Library	Downtown Transit Ctr Arrive	Downtown Transit Ctr Depart	California at Taft	Kennedy Lib.	
Labor Day - June 12 / Monday - Friday	Daytime	Start	**7:02**	7:09	7:15	7:20	7:26	AM
		Every 30 mins	:02	:09	:15	:20	:26	
			:32	:39	:45	:50	:56	
		End	6:02	**6:09**				PM
	Evenings	Start	**6:32**	6:39	6:45	6:50	6:56	PM
		Hourly	:32	:39	:45	:50	:56	
		End	10:32	10:39	10:45	10:50	**10:56**	PM
	Saturdays	Start			**8:45**	8:50	8:56	AM
		Hourly	:32	:39	:45	:50	:56	
		End	5:32	5:39	5:45	5:50	**5:56**	PM
June 15 - Labor Day / Mon - Fri.		Start			**8:45**	8:50	8:56	AM
		Hourly	:32	:39	:45	:50	:56	
		End	5:32	5:39	5:45	5:50	**5:56**	PM

Route 6b serves the following stops *(Transfer Options)*:

- **Kennedy Library** *(4, 5, 6a)* e
- Performing Arts Center
- Grand at McCollum
- Grand at Wilson
- Mill at Park
- Mill at Pepper
- Phillips at Pepper
- Mill at Johnson
- Mill at Santa Rosa
- **Downtown Transit Center** *(all except 6a)* e
- Mill at Santa Rosa
- Mill at Johnson
- Phillips at Pepper
- Mill at Pepper
- California at Phillips
- **California at Taft**
- **Kennedy Library** (4, 5, 6a) e

Figure 67: SLO Transit Route 6B Bus Schedule

4.4.3 Origin-Destination Estimation Applications for Other Routes

For routes with a wider range of origins and destinations, it is not recommended to use the same procedure that was used to generate the OD matrices for Routes 6A and 6B. The OD matrices for Route 6A and 6B were generated under the assumption that at least the origin or destination is known. For other routes, the origin or destination is not assumed. For example, Route 4 and 5 run a single loop in reverse direction to each other that covers the northwest, north, south, and southwest areas of San Luis Obispo. The routes serve multiple neighborhoods and travel demands including Cal Poly, Laguna Lake Middle School, Downtown San Luis Obispo, the San Luis Obispo Train Station, shopping centers, and numerous residential neighborhoods. These zones are marked by quarter-mile radius circles along Routes 4 and 5 in Figure 68.

To estimate the origin and destination travel flows using Bluetooth data, it is recommended to use a statistical analysis software to group by trip start time and end time, then group each time into a time frame. Then, ridership flows could be identified based on travel between the quarter-mile radius zones. It is possible to accomplish this by matching the Bluetooth detection time stamps with the time stamp of the GPS data collected on the SLO Transit buses during service hours. The Bluetooth detection time stamps could also be matched with the APC events which provide information on the arrival and departure times at each bus stop based on the passengers boarding or exiting.

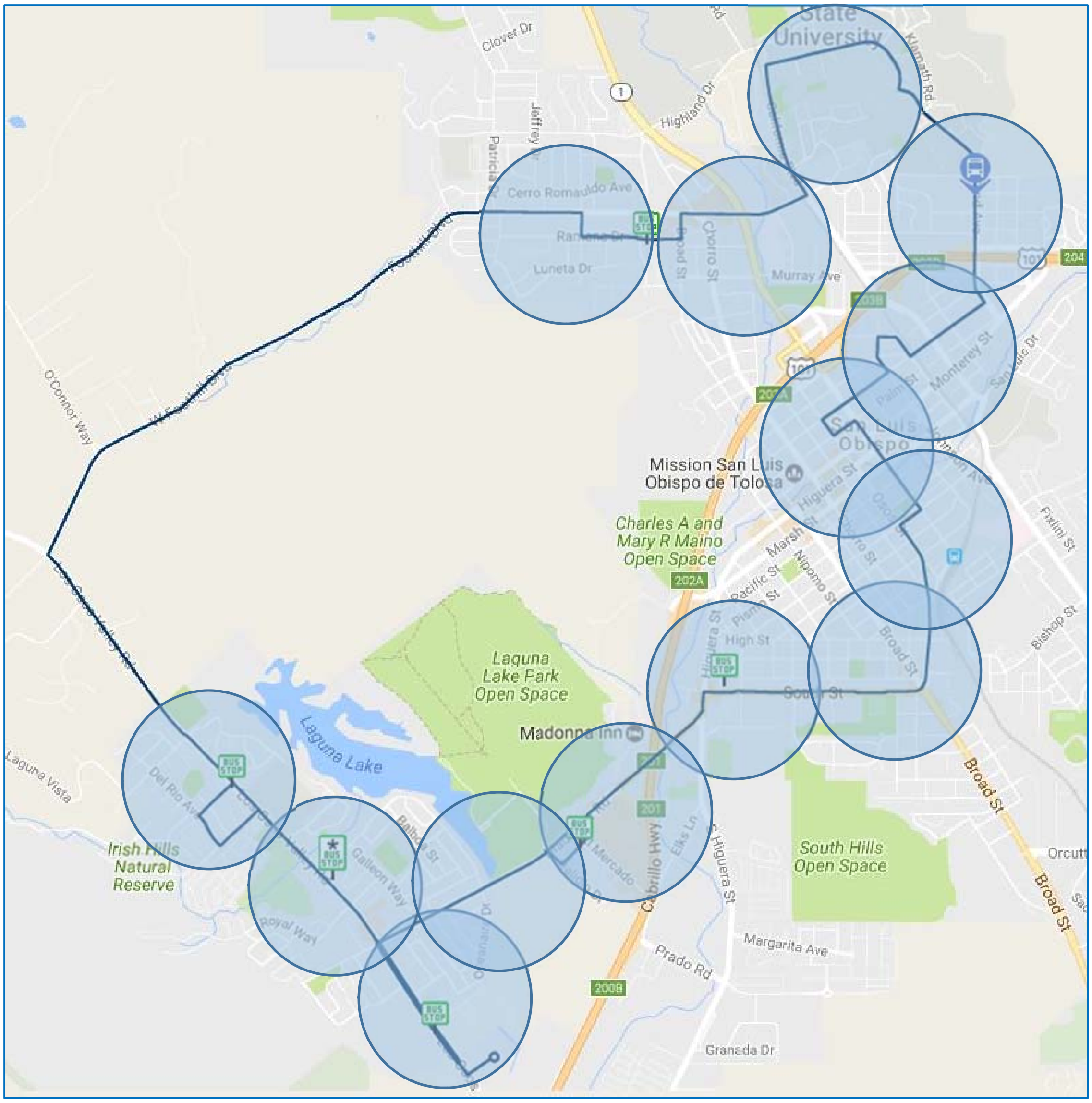


Figure 68: SLO Transit Route 4 and 5 Routes with Quarter-Mile Radius Zones

5. CONCLUSIONS

The conclusions describe possible applications of wireless BlueMAC devices and automatic passenger counters for transit data collection. A field experiment was designed and conducted, and a set of data filtering methods were developed specific toward the data set. The filtering methods were applied to the Bluetooth data to extract counts of unique passenger information and to compare the filtered data to the ground-truth APC data.

Both APC and BlueMAC data collection methods have a low initial investment and the potential for real-time monitoring. This wireless sensing method potentially has advantages over traditional data collection methods including:

- Automated, wireless data collection and upload
- Observed travel behavior in real-time
- Minimal maintenance after programming and installing the hardware
- Low costs of hardware, software, and installation
- Short programming and installation time

5.1 APC and Bluetooth Data Collection and Filtering

The methods and results described provide a reasonable illustration of the possibilities with wireless Bluetooth detection data. The study showed the ability of the wireless devices to collect information about trip behavior and travel flow. This study showed that the number of passengers carrying a Bluetooth-enabled device was sufficient to provide a sample of the ridership population. The boarding and alighting locations of the passengers could be inferred from Bluetooth data supplemented with the APC data and the SLO Transit GPS data for device locations.

Regarding data collection, the APC and MAC address detection requires no effort from the driver or an onboard survey. The efforts arise in the device installation, probe runs, and data filtering and cleaning. Because the BlueMAC data only recorded time stamps and MAC addresses, the data needed to be filtered to retain the actual passenger trips and remove the extraneous detections.

Both BlueMAC and APC data could be used as data collection methods in transportation engineering, but for different purposes. The novelty of the Bluetooth data collection method is that trip durations could be recorded due to the unique MAC addresses. Using the MAC addresses, it is also possible to estimate the exact stop where an individual device boards or alights a bus. Based on the captured trips, it is possible to infer OD demand as well as travel behavior by considering trip duration. It is necessary to match the detection timestamp with the bus GPS coordinates to determine origin-destination patterns. With APC data, passenger counts could be recorded and used to determine bus stops with the highest utilization and ridership patterns. APC data provides counts at each bus stop, so determining the exact route of passengers requires inferences and assumptions of the origin or destination. Used together, Bluetooth and APC data could provide key information in transit planning and operations. However, as discussed in more detail in Section 5.3.1, relying on the possession of BT-enabled devices may not lead to a random sample, resulting in misleading travel demand patterns. While it was beyond the scope of this work, it may lead to some equity issues as well (See Section 5.3.1).

5.1.1 Farmer's Market Analysis

Using APC data, the SLO Transit Routes that connect Cal Poly to Downtown San Luis Obispo were analyzed on Tuesday and Thursday nights. Thursday nights were analyzed to observe ridership changes due to the weekly night Downtown San Luis Obispo Farmer's Market. The APC data for three Tuesdays and three Thursdays revealed a 40% increase in passengers from Tuesday to Thursday from 5 PM to 10 PM. The data from the BlueMAC detectors were not used for the Farmer's Market analysis because the route service times for the buses ended at the Farmer's Market start time based on the Daily Dispatch Logs. Since the service time ended during the Farmer's Market start times, the PM times beyond the bus log out times were filtered out. The buses were likely switching from the day shift to the night shift, accounting for the service time ending.

Tactical urbanism may be an effective way for cities to sustain transit that otherwise may be deemed unviable. SLO Transit deploys an effective bus system that serves thousands of university students and local residents. Events such as the SLO Farmer's Market that fit under the broad umbrella of tactical urbanism can bring communities together and encourage people to ride transit.

5.2 Origin-Destination Matrix Generation from APC and BlueMAC Data

The procedure in generating the OD matrices were time-consuming for both APC and BlueMAC data. Each origin-destination trip required manually counting the passengers on the APC and BlueMAC data. The matrices display similar trip patterns: the passenger counts were highest at the same bus stops. However, because of the limited sample size of the Bluetooth observations, a direct comparison cannot be made between the two matrices. A few days of data are not a sufficient sample size to reliably infer

passenger ODs. For future studies, much longer data collection period is suggested to obtain more meaningful results, and the data should be counted using a software package such as SAS to generate total passenger counts more efficiently.

5.3 Limitations of Research

Although this study indicates the potential of passenger OD estimation through wireless Bluetooth detection, there are several limitations that may limit its usefulness to the transit agencies. Limitations of the data sources, filtering procedures, and passenger OD estimation are described in the next subsection. In the data filtering process, it was assumed that each passenger carried only one mobile device with Bluetooth. Some individuals carry multiple mobile devices, and this was witnessed through probe runs, onboard surveys, and observations as a transit passenger. Furthermore, most of the passengers of SLO Transit are university students, and many carry laptops to do homework, take notes in class, use social media, and browse the Internet. This assumption creates a source of error in estimating origin-destination patterns. While the devices such as the smartphones and tablets are seemingly ubiquitous, their distribution is likely influenced based on socio-economic characteristics. Relying solely on these devices in a diverse environment may lead to overestimating transit demand to or from stops serving more affluent neighborhoods.

Furthermore, the detected population of devices represents a select sample of the entire ridership population. This select sample of passengers may have different travel patterns than the rest of the ridership population. A much longer data collection period is recommended to obtain more meaningful results for the data.

5.3.1 Bluetooth Data

There are technological and functional differences between the Bluetooth and APC data collection methods. These differences should be considered when improving the data collection and processing methods presented in this thesis. APC data collection is more exact and tracks the exact moment, location, and the number of passengers boarding and alighting the buses. Bluetooth has a larger detection range, which resulted in a greater number of detections that required filtering and added uncertainty to the data. The characteristic of a larger detection range is useful in cases where a large area of detection is necessary – such as a parking lot or transit center. Its real-time data capabilities could be used for special events or natural disasters. A deployed system in these types of scenarios would allow for rapid understanding of the magnitude of travel changes and demands, then help with adjusting resources such as redesigning bus networks temporarily.

Bluetooth provided a good sample of onboard passenger data, but is limited in sample size compared to the APC data because it captures only a select population of the passenger ridership: passengers with enabled Bluetooth devices. Moreover, comparison between the numbers of unique passengers estimated using filtered Bluetooth data and those with APC data did not reveal a consistent pattern of difference between the estimates from the two sources. It led us to believe that this select population of passengers with enabled Bluetooth devices may not be a random sample of passengers.

5.3.2 Data Filtering Methods

The data filtering methods pose uncertainty in either direction – the filters could be too aggressive or not aggressive enough in honing data sets. Data filtering also poses

uncertainty in either direction; filtering methods could be either too aggressive or not aggressive enough in narrowing data sets. For example, the filter for the detection duration for certain routes needed to be adjusted based on the trip time for each loop.

5.3.3 Privacy Implications

The use of Bluetooth has privacy implications. The system for the data collection tracks individual passenger behavior over time which also tracks precise information on passengers' locations. This type of information could be misused for harmful intents and purposes. Transit companies and agencies must ensure that trip data are secured because the issue of privacy on public transit is very sensitive. If the public is made aware of privacy issues of Bluetooth and data collection, they may be more likely to stop using that technology or disable it. On the other hand, as new technology becomes available to users, people will be motivated to adopt these new technologies on a daily basis. However, the Bluetooth data collection provides an opportunity for potential bus service personalization and one-on-one interactions with passengers.

5.4 Further Analysis and Research

There should be further consideration in improving the data collection and analysis methods utilized in this study. More work is also necessary to determine the optimal hardware settings and placement of the device on the bus based on each scenario. For example, a second Bluetooth device could be placed on the back of the bus and simultaneously collect data with a detector installed at the front of the bus.

Further research is needed to validate the data filtering procedures on the SLO Transit bus network or the bus system in analysis. One of the challenges that must be addressed in future work is the extraneous detections that occur during the data collection

period. Further research is recommended for large-scale bus systems in urban areas. It is suggested to study one specific route for a span of multiple weeks or a month. Because of this consideration, multiple iterations of the data filtering should be conducted to minimize discarding useful data and to optimize the ideal filter system for each specific route. In this thesis, multiple iterations of trip duration filters were tested, and further research could be done by testing iterations of other filters such as minimum trip duration or number of detections.

The data filtering methods need to be more robust for bidirectional routes. The bi-directional Route 4 and 5 of the SLO Transit bus system were not analyzed in this study because these routes have two buses on each route at a time. These four sub-routes are called Route 4A, 4B, 5A, and 5B. The APC data combines the passenger counts for the two buses on each route and provides reports of the combined data. Without the counts from each passenger bus, the APC data was unable to be compared to the BlueMAC data from the same bus, as intended in this study. For future studies, it is recommended to study bi-directional routes to consider factors such as buses picking up each other's passengers' data as they pass each other or stop on opposite sides of the road. There may also be issues, due to the large range of detection, associated with bus stops located on opposite sides of the road.

Creating a GIS map and pairing the bus GIS coordinates to the BlueMAC time stamps would be beneficial for a complete picture of the SLO Transit bus network. The detections could be mapped and travel paths could be generated on the map. In addition, data collection and post-data filtering layers would be beneficial in visualizing the data

and communicating information to the public and clients. The map could be further detailed to show the origin-destination patterns of transit ridership.

Future studies should involve collaborative efforts with cities of similar size and characteristics. Multiple cities could deploy BlueMAC devices onto buses at the same dates and times, filter the data, and make comparisons on the ridership patterns based on the data. The collaboration efforts would include sharing the BlueMAC data, ideas on optimal device placement and power sources for the devices, and observations on the BlueMAC data. The comparison between the cities' BlueMAC data could provide conclusions on transit ridership between cities of similar characteristics.

With rapidly-evolving data collection technologies, transit data collection methods could expand beyond the traditional onboard survey. The lessons learned from this study could be expanded to provide a robust and detailed data source for transit operations and planning.

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APPENDICES

APPENDIX A: PASSENGER SURVEY RESPONSES

Age	Gender	Daily Trips	Wait Time	Use Devices?	Device Use	Bluetooth?	Disabled?
21	F	2	5	Y	D	N	A
20	F	2	7	Y	C	Y	
21	M	2	5	Y	C	Y	
22	M	2	5	Y	C	Y	
21	F	2	5	Y	C	N	C
23	M	2	5	Y	C	N	A
21	M	2	2	Y	D	Y	
21	M	4	5	Y	E	N	C
21	M	2	10	Y	E	Y	
21	M	1	5	Y	D	Y	
26	M	2	5	Y	E	Y	
20	M	4	7	Y	E	Y	
20	M	4	15	Y	E	N	A
20	F	4	10	Y	E	N	A
23	M	2	10	Y	E	N	C
19	F	2	5	Y	D	Y	
21	M	2	10	Y	E	N	A
21	M	2	10	Y	D	N	C
30	M	3	15	Y	E	N	C
21	M	4	5	Y	D	Y	
21	F	4	5	Y	D	Y	
20	M	2	10	Y	D	Y	
21	F	3	7	Y	E	N	A
23	M	1	5	Y	E	Y	
31	M	3	5	N		N	C
20	F	2	10	Y	E	N	C
20	F	4	20	Y	E	N	A
21	M	2	30	Y	E	N	A
22	F	2	5	Y	E	Y	
21	F	4	5	Y	D	N	A
21	M	2	1	Y	D	N	A
22	M	2	1	Y	C	N	C
19	F	2	20	Y	E	Y	
27	M	1	20	Y	D	N	C
19	F	2	10	Y	D	N	A
21	F	2	15	Y	A	Y	
20	M	4	15	Y	E	N	A
60	F	2	5	Y	D	Y	
21	M	4	15	Y	E	Y	
54	F	10	20	Y	B	N	B
26	M	4	10	Y	E	N	C
22	M	2	10	Y	D	N	C
20	F	2	10	Y	A	Y	
20	M	2	10	Y	D	N	C
22	F	2	15	Y	D	N	C
22	M	2	10	Y	D	N	A
22	M	2	5	Y	E	N	A

21	M	2	20	Y	D	N	A
21	M	2	30	Y	E	N	A
21	M	2	30	Y	E	N	A
22	F	4	12	Y	E	N	C
19	F	1	10	Y	C	N	A
21	F	4	30	Y	D	Y	
19	M	2	10	Y	E	N	A
23	F	2	10	Y	E	Y	
24	M	2	1	Y	A	N	C
20	M	2	10	Y	D	N	A
19	M	2	5	Y	D	N	A
22	M	2	5	Y	D	N	C
21	M	2	10	Y	D	Y	
22	M	2	10	Y	E	N	C
22	F	2	15	Y	D	N	A
20	F	4	5	Y	A	N	C
19	F	1	15	Y	A	N	C
22	M	2	5	Y	D	N	C
21	F	2	30	Y	D	N	C
20	F	4	10	Y	D	N	A
21	F	1	7	Y	C	N	A
22	M	2	10	Y	D	N	A
19	M	4	15	Y	D	N	C
19	M	3	20	Y	D	N	A
21	F	4	10	Y	E	N	C
21	M	4	3	Y	D	N	A
20	M	4	5	Y	C	N	C
21	F	1	10	Y	D	N	A
21	F	2	5	Y	A	N	A
22	F	4	20	Y	E	N	C
22	F	2	30	Y	A	Y	
22	F	2	10	y	D	N	C
21	M	2	15	Y	C	N	C
21	F	4	20	N		N	A
21	F	2	5	Y	C	N	C
23	M	2	5	Y	D	N	A
21	M	2	15	Y	E	Y	
21	F	2	5	Y	A	N	C
20	F	4	25	Y	D	N	A
21	F	2	3	Y	D	N	C
20	F	2	10	Y	A	N	A
22	M	2	4	Y	C	Y	
22	F	2	5	Y	D	N	A
20	F	2	10	Y	A	Y	
21	F	2	5	Y	A	N	C
21	F	2	5	Y	E	N	C
22	M	2	7	Y	E	N	C
28	M	2	5	Y	C	N	C

21	F	2	1	Y	A	N	A
20	F	1	30	Y	A	Y	
19	F	1	30	Y	A	N	C
22	F	2	15	Y	D	N	C
21	M	2	15	y	A	N	C

Device use		Bluetooth use	
A	TEXT	A	BATTERY LIFE
B	PHONECALL	B	PRIVACY
C	INTERNET	C	NO NEED
D	ENTERTAINMENT		
E	ALL OF THE ABOVE		

APPENDIX B: SAMPLE SAS CODE

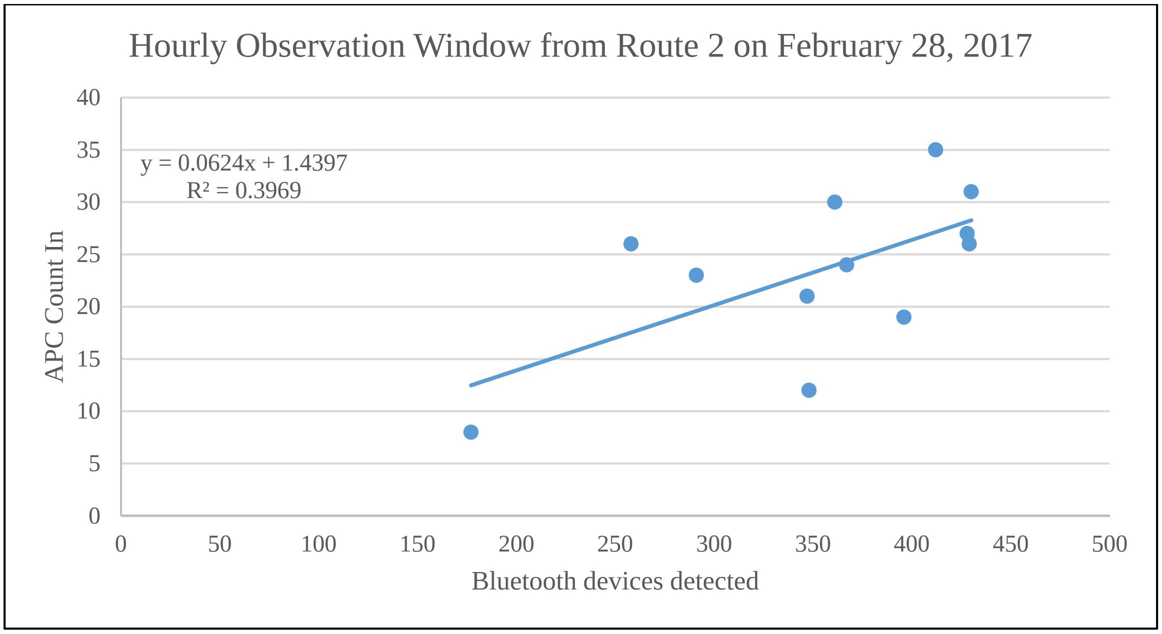
```
proc import datafile="filelocation"
out=data
dbms=csv
replace
;
datarow=5;
getnames=no;
run;
data data;
format Capture_Time datetime.;
set data;
if substr(VAR2,4,1)='E' & notdigit(substr(VAR2,5,2))~='' then delete;
MAC_Address=VAR2;
Capture_Time=VAR1;
drop VAR1 VAR2 VAR3 VAR4;
run;
data data;
set data;
if (Capture_Time>=DHMS(mdy(3,day,17),hour,minute,0) and
Capture_Time<=DHMS(mdy(3,day,17),hour,minute,0)) or
(Capture_Time>=DHMS(mdy(3,day,17),hour,minute,0) and
Capture_Time<=DHMS(mdy(3,day,17),hour,minute,0));
run;

proc sql;
create table sums as
select MAC_Address, count(MAC_Address) as N
from data
group by MAC_Address;
quit;
proc sql;
create table next as
select Capture_Time, data.MAC_Address, N
from data
left join
sums
on data.MAC_Address=sums.MAC_Address
;
quit;

proc sort;
by MAC_Address Capture_Time;
where N>5;
run;
```

```
data next;
set next;
by MAC_Address Capture_Time;
if first.MAC_Address=0 then do;
sec=int(intck('second',Previous_Capture_Time,Capture_Time));
end;
Previous_Capture_Time=Capture_Time;
retain Previous_Capture_Time;
run;
data next;
set next;
by MAC_Address;
if first.MAC_Address=1 then trip=0;
if sec>2400 then do;
trip=trip+1;
sec=.;
end;
retain trip;
run;
proc sql;
create table grouping as
select MAC_Address, trip, sum(sec) as seconds, count(trip) as N,
min(Capture_Time) as Start, max(Capture_Time) as End
from next
group by MAC_Address, trip;
quit;

data final;
format start dateampm. end dateampm.;
set grouping;
if seconds<2400;
if seconds>180;
time=seconds;
drop seconds;
run;

data final;
format time mmss.;
set final;
drop trip;
run;

proc export data=final
outfile="C:/Users/mcolli22/Downloads/dataFinal.csv"
dbms=csv
```

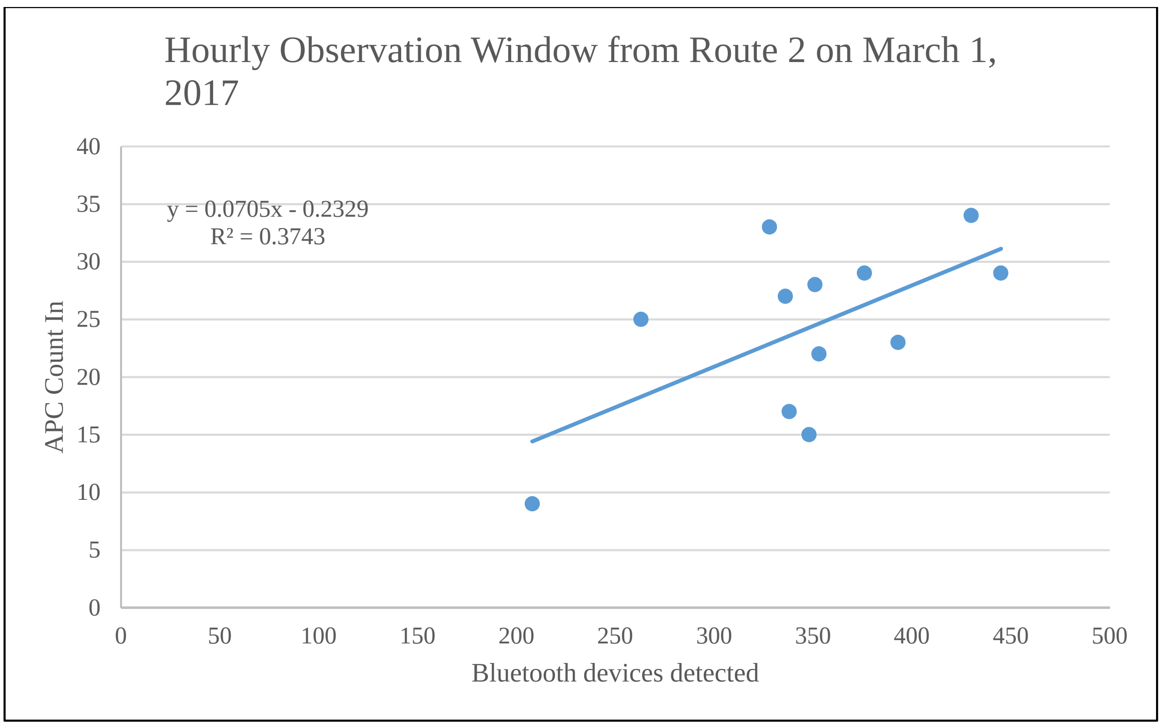
```
replace;
run;

proc sql;
create table eachtime as
select Capture_Time, next.MAC_Address, time
from next
join
final
on next.MAC_Address=final.MAC_Address and next.trip=final.trip;
quit;
proc sort;
by Capture_Time;
run;
data finalhour;
set eachtime;
hours=floor(intck('hour',DHMS(mdy(3,7,17),6,0,0),Capture_Time))+6;
min=floor(intck('min',DHMS(mdy(3,7,17),6,0,0),Capture_Time)/15);
run;
proc sql;
create table counts as
select count(distinct MAC_Address) as people, hours
from finalhour
group by hours;
quit;
data hourly;
format hour dateampm.;
set counts;
hour=intnx('hours',dhms(mdy(3,7,17),0,0,0),hours);
drop hours;
run;

proc sql;
create table minutes as
select count(distinct MAC_Address) as people, min
from finalhour
group by min;
quit;
data minutely;
format minute dateampm.;
set minutes;
minute=intnx('minute',dhms(mdy(3,7,17),6,0,0),min*15);
drop min;
run;

proc export data=hourly
```

```
outfile="C:/Users/mcolli22/Downloads/dataFinalhour.csv"
dbms=csv
replace;
run;

proc export data=minutely
outfile="C:/Users/mcolli22/Downloads/dataFinalminute.csv"
dbms=csv
replace;
run;

proc print data=data (obs=1000);
run;
```

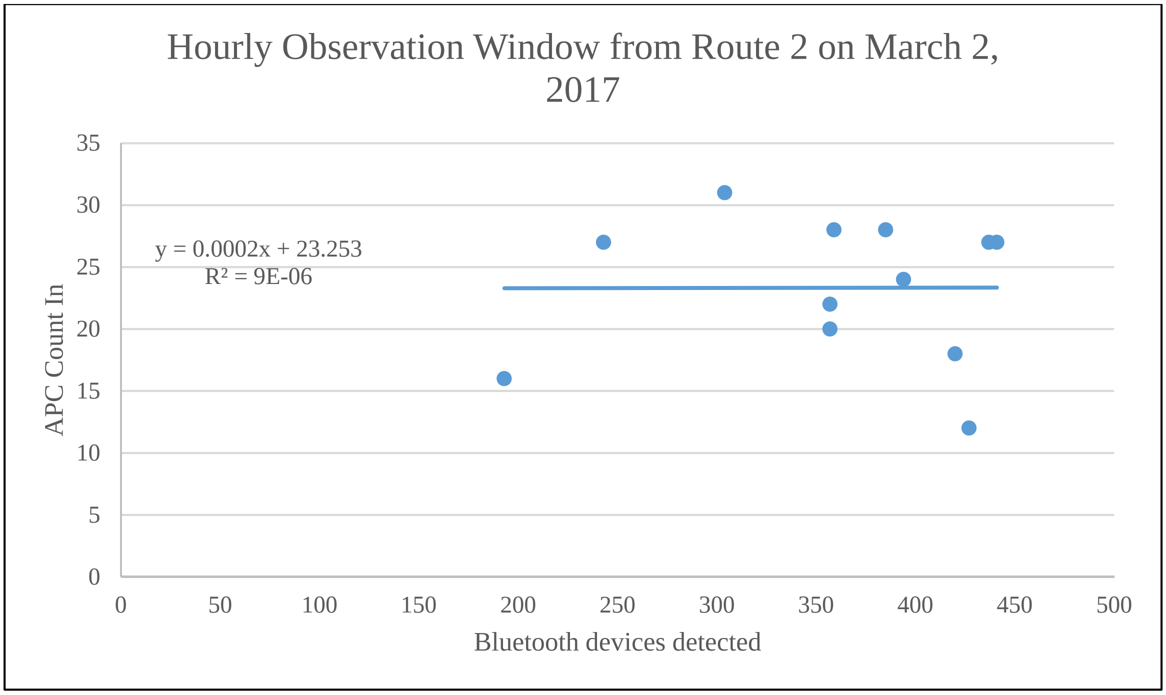
APPENDIX C: HOURLY OBSERVATION GRAPHS



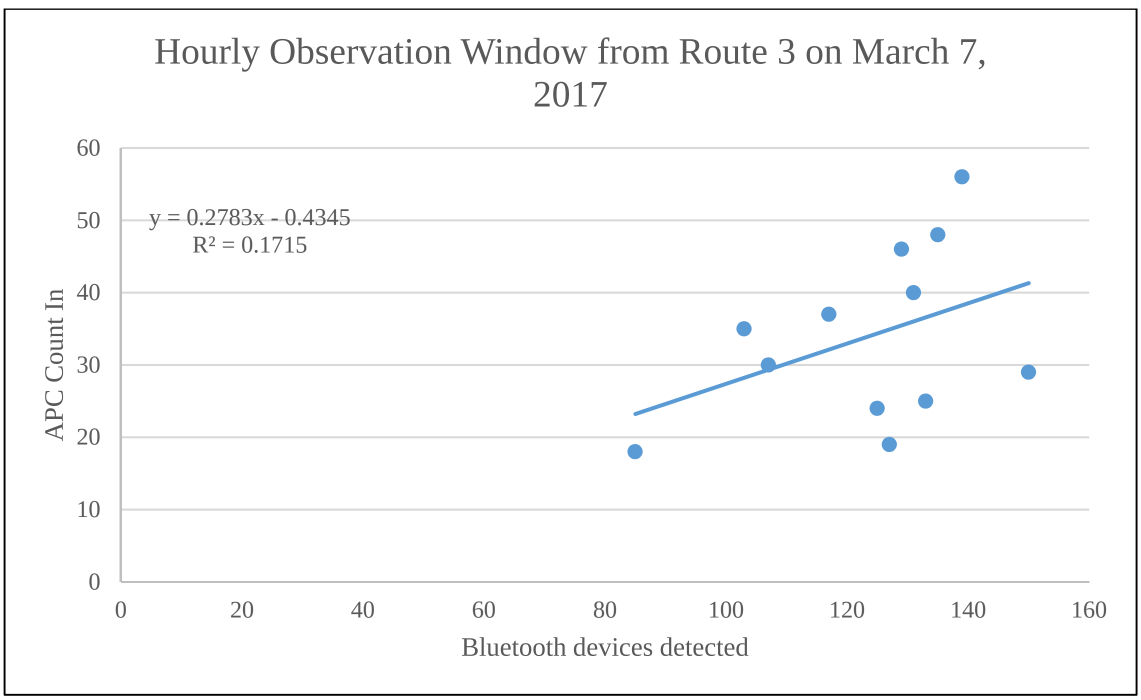
Correlation Between Trips Captured by Bluetooth and by APC for Route 2 on February 28, 2017



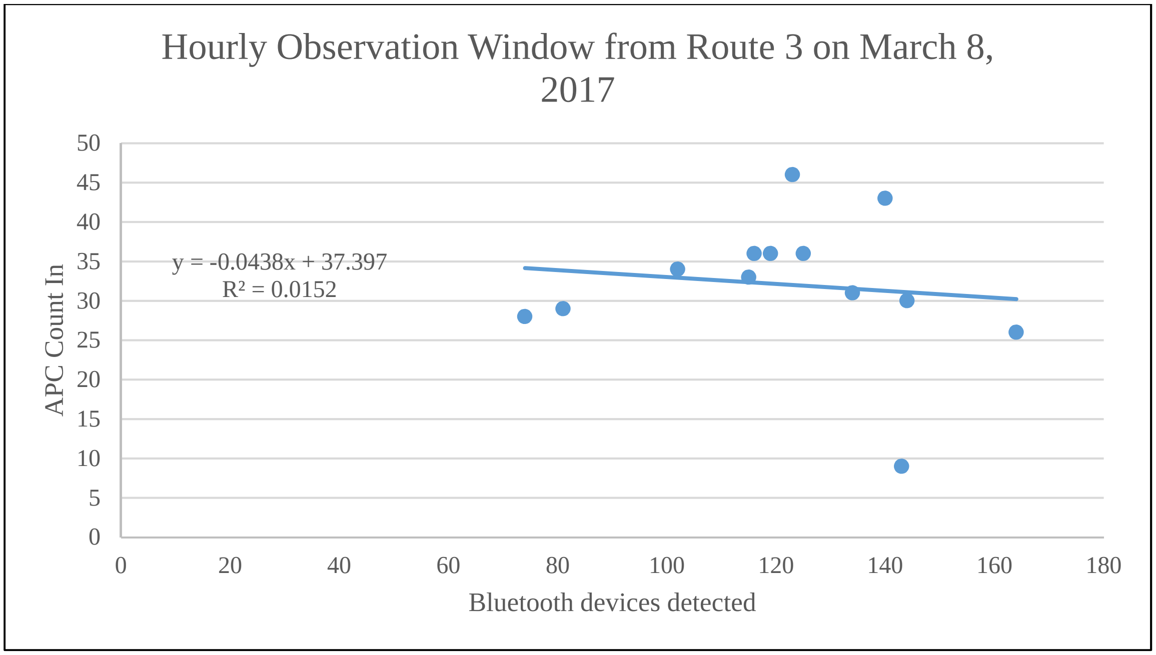
Correlation Between Trips Captured by Bluetooth and by APC for Route 2 on March 1, 2017



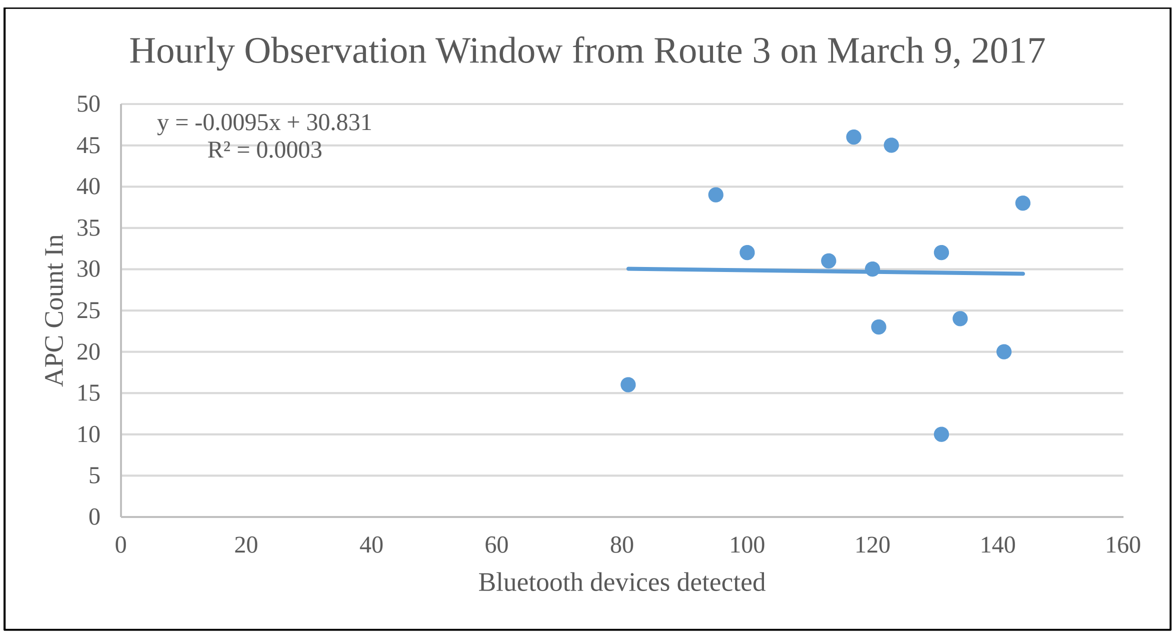
Correlation Between Trips Captured by Bluetooth and by APC for Route 2 on March 2, 2017



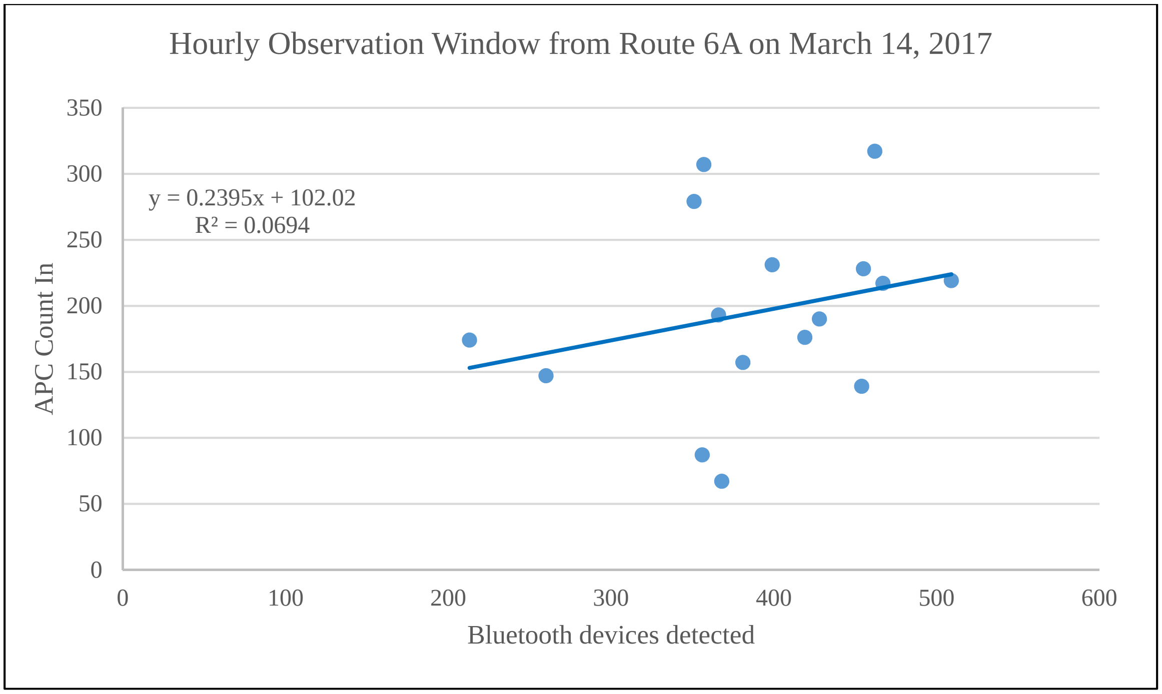
Correlation Between Trips Captured by Bluetooth and by APC for Route 3 on March 7, 2017



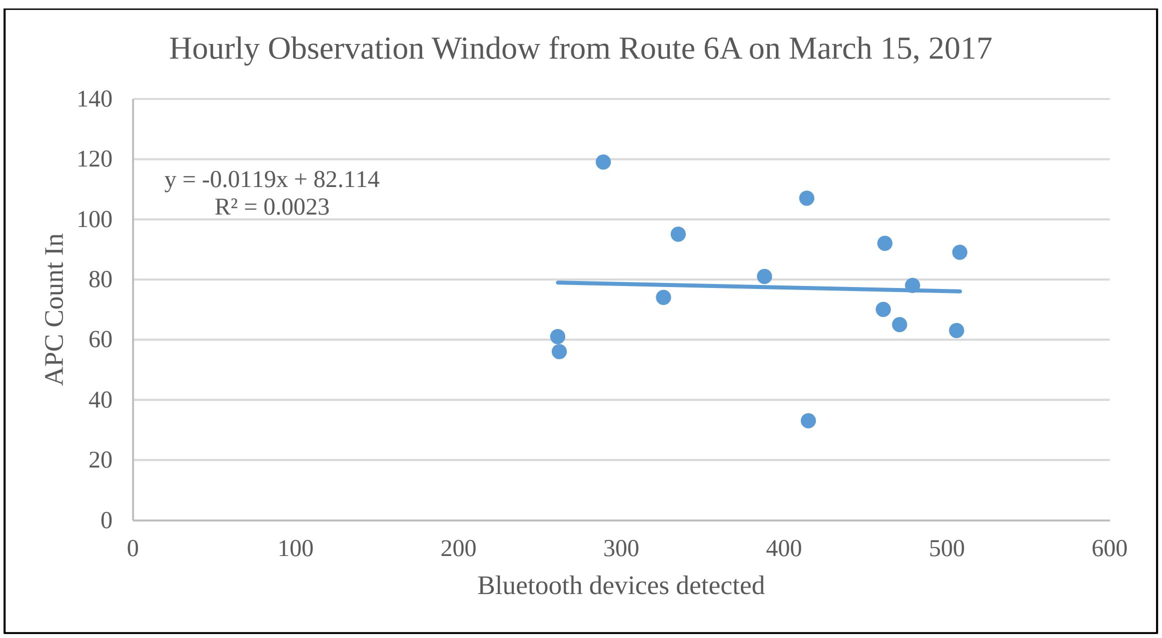
Correlation Between Trips Captured by Bluetooth and by APC for Route 3 on March 8, 2017



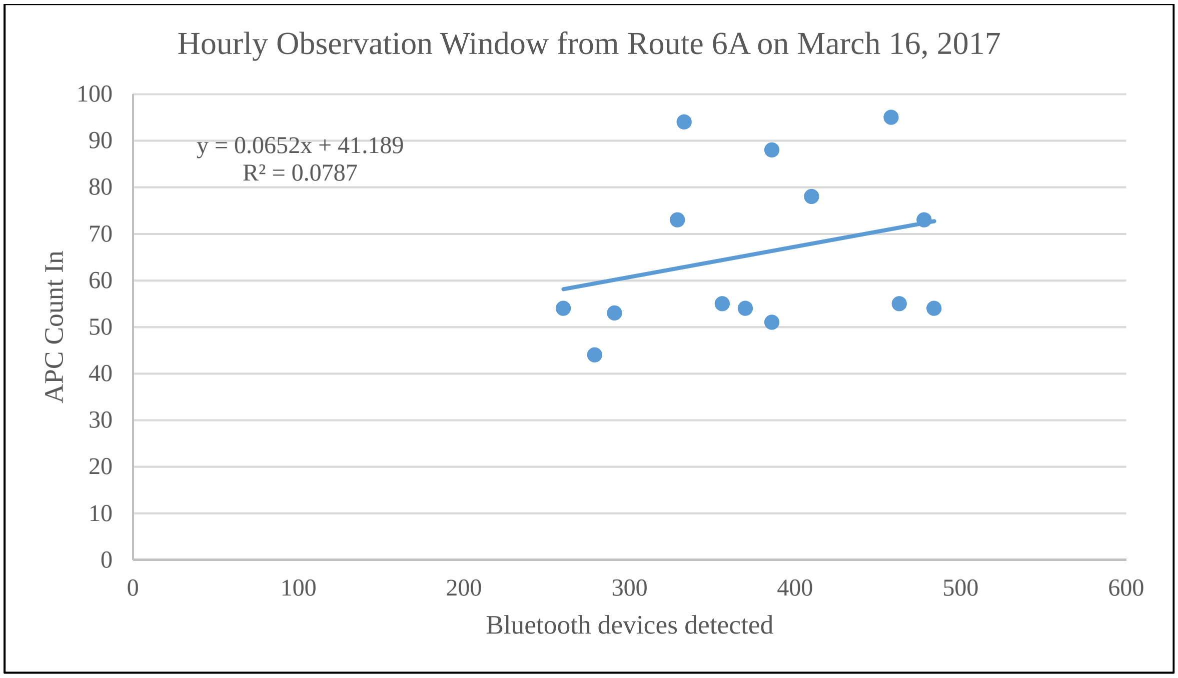
Correlation Between Trips Captured by Bluetooth and by APC for Route 3 on March 9, 2017



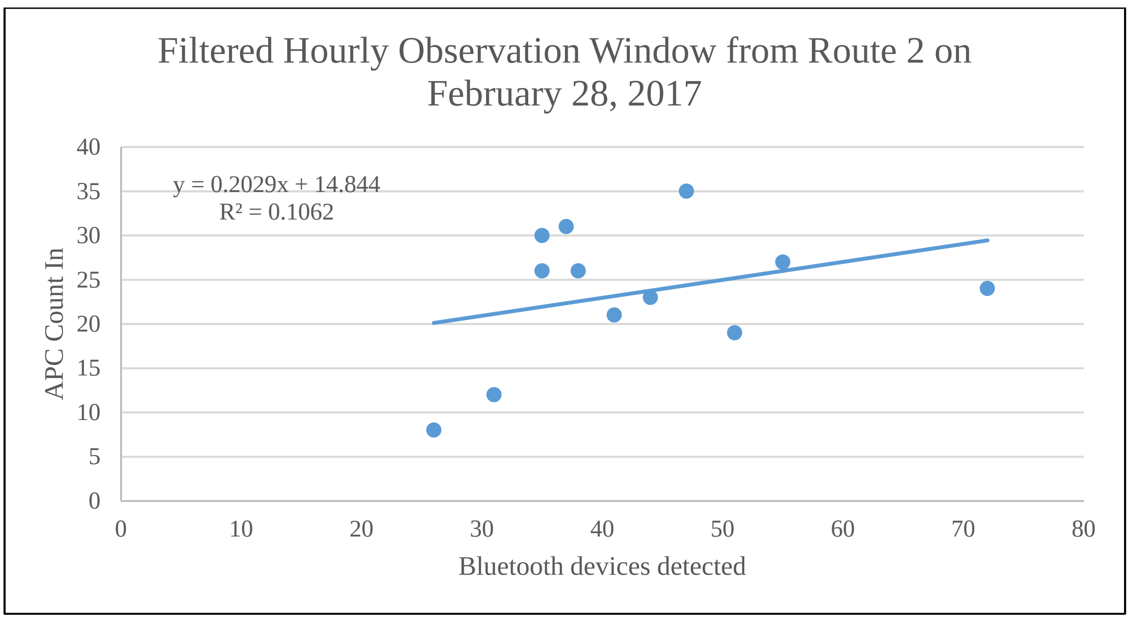
Correlation Between Trips Captured by Bluetooth and by APC for Route 6A on March 14, 2017



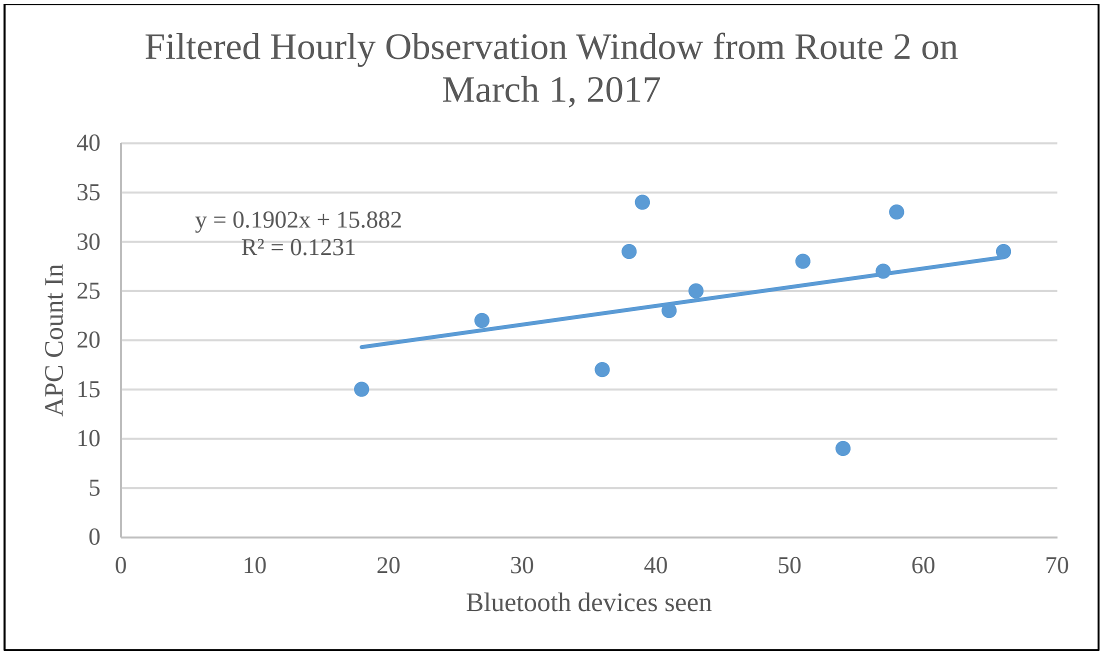
Correlation Between Trips Captured by Bluetooth and by APC for Route 6A on March 14, 2017



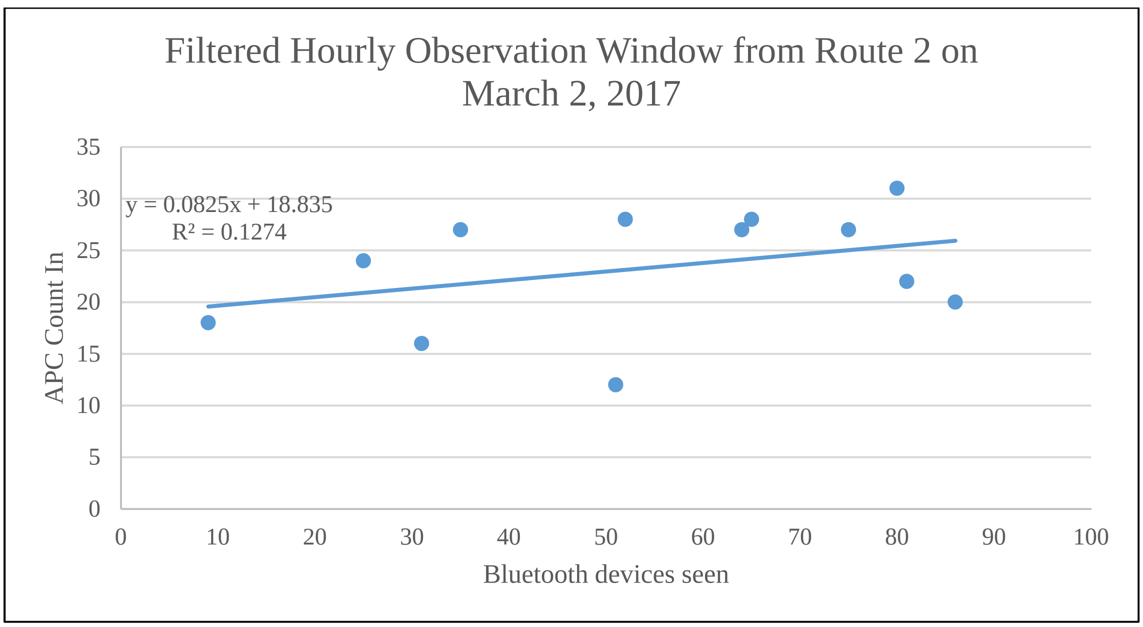
Correlation Between Trips Captured by Bluetooth and by APC for Route 6A on March 14, 2017



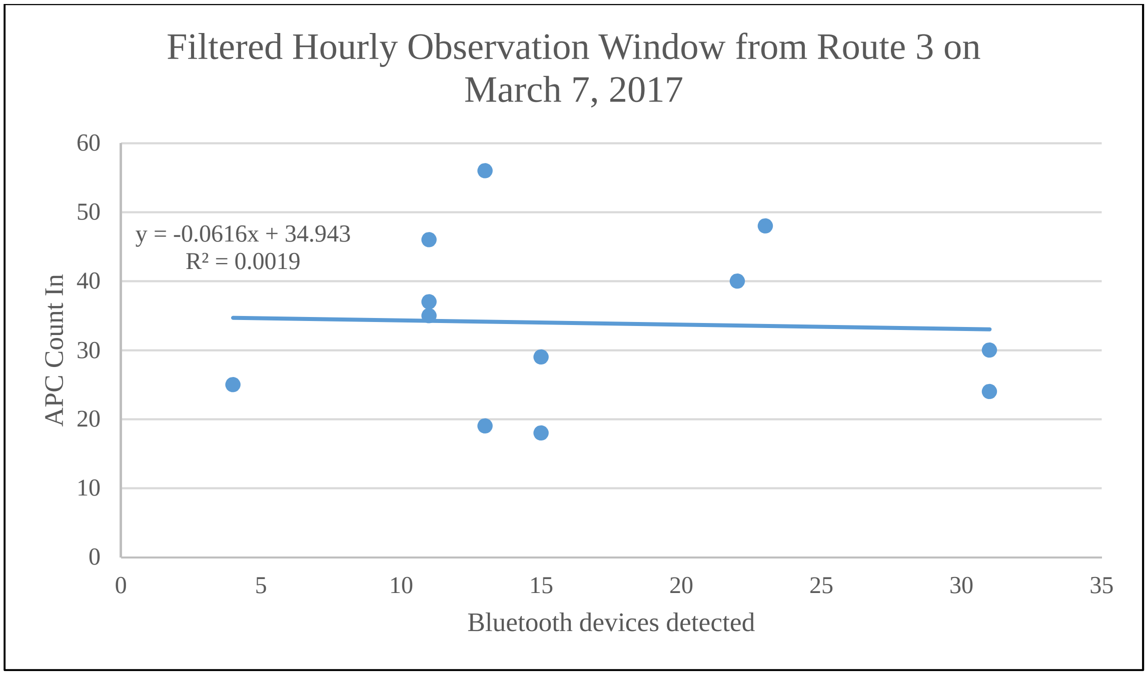
Correlation Between Trips Captured by Filtered Bluetooth Data and by APC for Route 2 on February 28, 2017



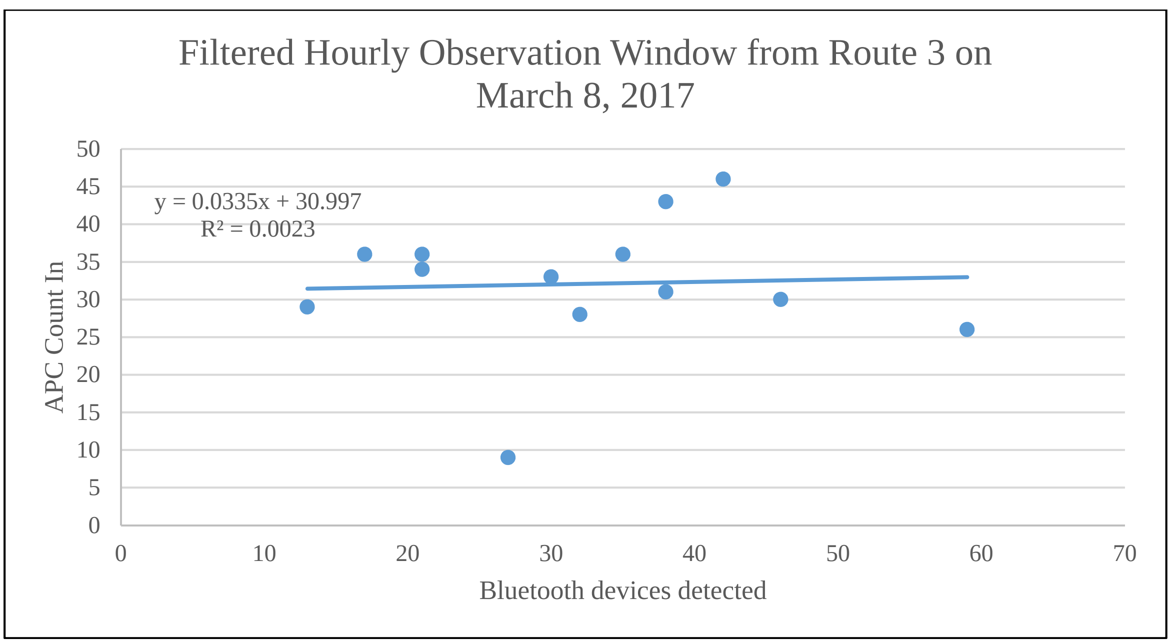
Correlation Between Trips Captured by Filtered Bluetooth Data and by APC for Route 2 on March 1, 2017



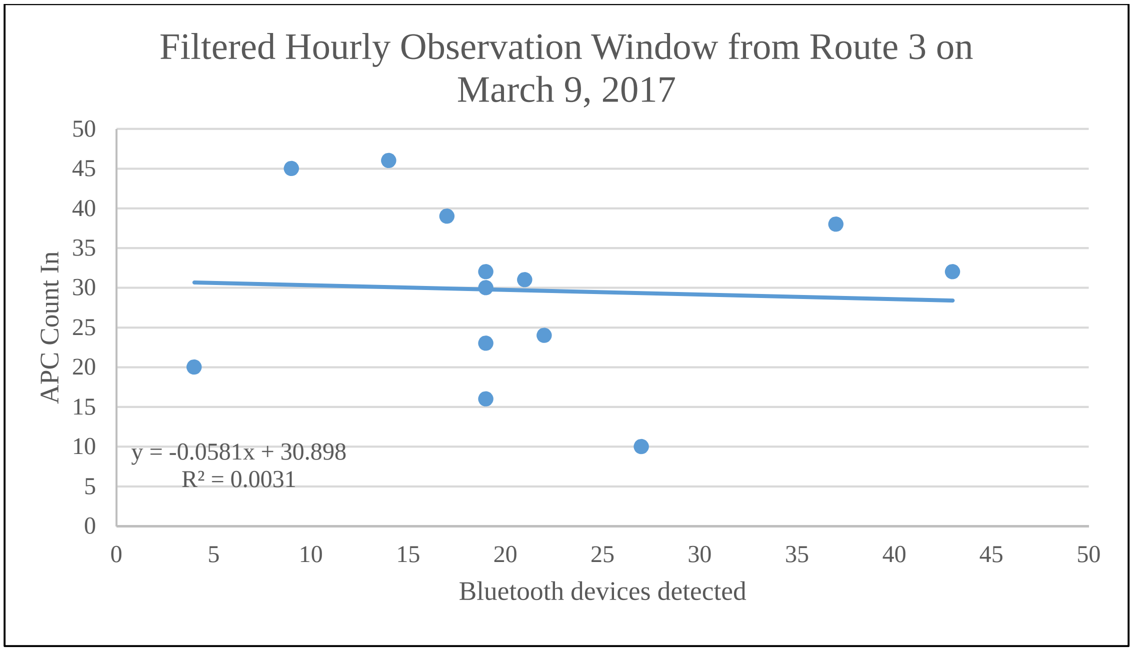
Correlation Between Trips Captured by Filtered Bluetooth Data and by APC for Route 2 on March 2, 2017



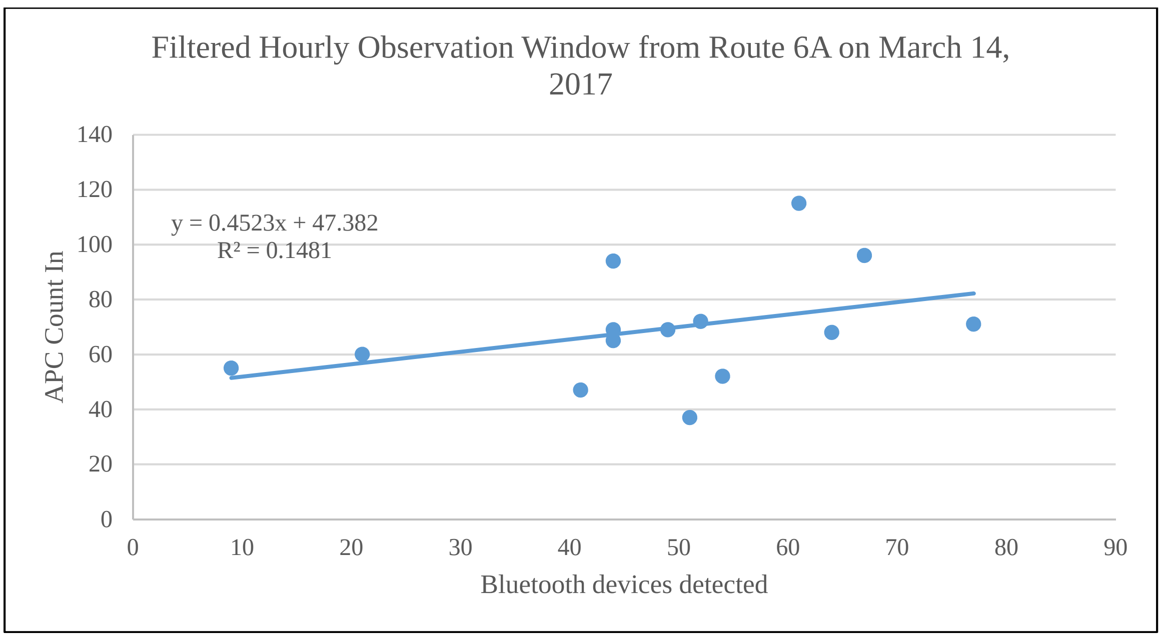
Correlation Between Trips Captured by Filtered Bluetooth Data and by APC for Route 3 on March 7, 2017



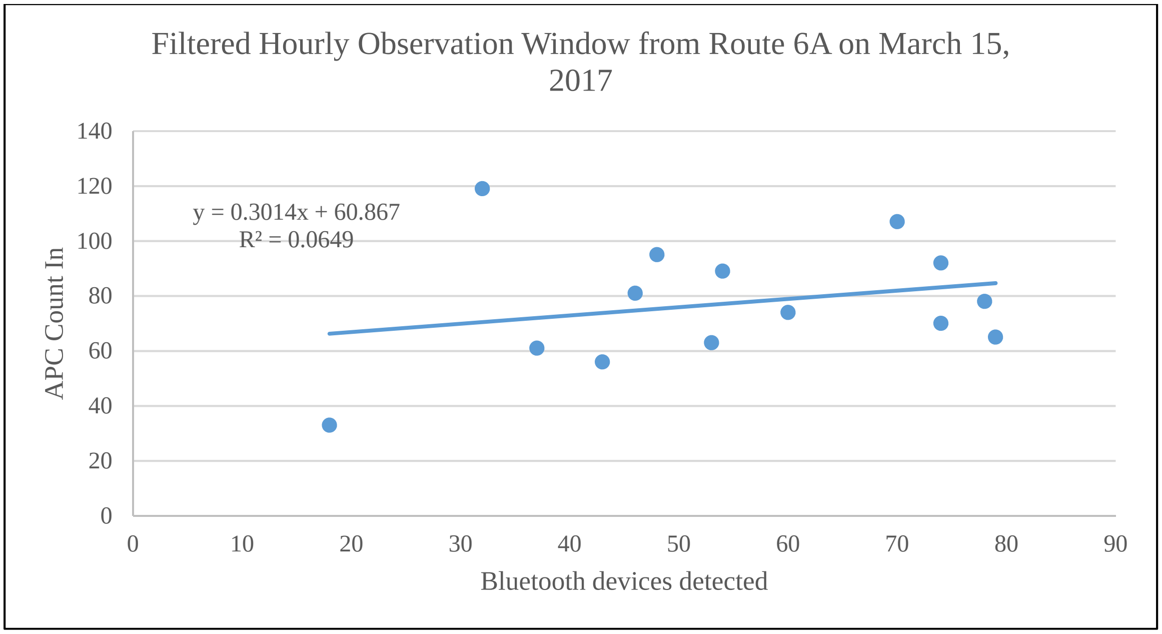
Correlation Between Trips Captured by Filtered Bluetooth Data and by APC for Route 3 on March 8, 2017



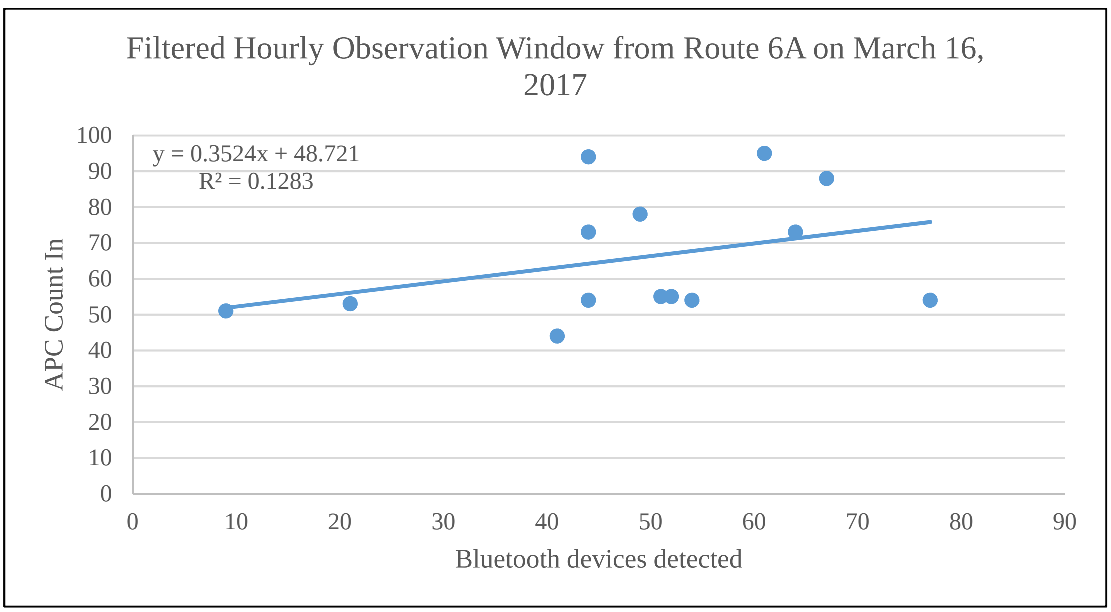
Correlation Between Trips Captured by Filtered Bluetooth Data and by APC for Route 3 on March 9, 2017



Correlation Between Trips Captured by Filtered Bluetooth Data and by APC for Route 6A on March 14, 2017



Correlation Between Trips Captured by Filtered Bluetooth Data and by APC for Route 6A on March 15, 2017



Correlation Between Trips Captured by Filtered Bluetooth Data and by APC for Route 6A on March 16, 2017

APPENDIX D: SLO TRANSIT WEEKLY ROUTE ASSIGNMENTS

Week	Day	Date	CP-02/ Bus 860	Log in	Log Out	CP-05/ Bus 862	Log in	Log out	CP-01/Bus 858	Log in	Log Out	CP-04/Bus 1264	Log in	Log Out	DIGI150/1365	Log In	Log Out
1	Tuesday	28-Feb	5A	6:21:00 AM	8:21:00 PM	2	6:02:00 AM	5:40:00 PM	6B	7:02:00 AM	8:10:00 PM	4A	6:34:00 AM	10:44:00 PM	3		
	Wednesday	1-Mar	5A	6:25:00 AM	8:21:00 PM	2	6:04:00 AM	5:40:00 PM	6B	7:02:00 AM	8:19:00 PM	4A	6:32:00 AM	10:44:00 PM	3 / 2/3 eve		
	Thursday	2-Mar	5A	6:21:00 AM	8:21:00 PM	2	6:03:00 AM	5:46:00 PM	6B	7:02:00 AM	8:15:00 PM	-			2/3 eve		
2	Tuesday	7-Mar	5A	6:21:00 AM	8:21:00 PM	2	6:01:00 AM	5:40:00 PM	6B	7:02:00 AM	6:15:00 PM	6A			3	6:03:00 AM	6:18:00 PM
	Wednesday	8-Mar	5A	6:20:00 AM	8:21:00 PM	2	6:03:00 AM	5:40:00 PM	6B	7:02:00 AM	6:15:00 PM	6A/B	-	-	3	6:04:00 AM	6:18:00 PM
	Thursday	9-Mar	5A	6:20:00 AM	8:22:00 PM	6A			6B	7:02:00 AM	8:18:00 PM	-			3	6:05:00 AM	6:18:00 PM
3	Tuesday	14-Mar	4B	6:10:00 AM	6:40:00 PM	2	6:03:00 AM	5:38:00 PM	6B			6A	7:15:00 AM	8:10:00 PM	-		
	Wednesday	15-Mar	4B	6:40:00 AM	6:40:00 PM	2	6:02:00 AM	5:49:00 PM	6B			6A	7:12:00 AM	8:10:00 PM	-		
	Thursday	16-Mar	4B	6:40:00 AM	6:38:00 PM	2	6:03:00 AM	5:50:00 PM	-			6A	7:20:00 AM	8:05:00 PM	-		
4	Tuesday	21-Mar	5B	6:20:00 AM	7:20:00 PM	-	-	-	4B	6:35:00 PM		4A	6:30:00 AM	10:44:00 PM	3		
	Wednesday	22-Mar	5B	6:20:00 AM	7:25:00 PM	-	-	-	6A/B			4A	6:32:00 AM	10:44:00 PM	2/3 eve		
	Thursday	23-Mar	5B	6:19:00 AM	7:17:00 PM	2/3 eve			6A			-			2		
5	Tuesday	28-Mar	6A	7:13:00 AM	8:05:00 PM	-	-	-	5A	6:20:00 AM	8:23:00 PM	-			3		
	Wednesday	29-Mar	6A	7:12:00 AM	8:10:00 PM	-	-	-	5A	6:20:00 AM	8:25:00 PM	-			2/3 eve		
	Thursday	30-Mar	6A	7:11:00 AM	8:05:00 PM	-	-	-	-			-			2		

APPENDIX E: ORIGIN-DESTINATION MATRICES

Thursday, 3/16/17 5:10pm and 5:40pm runs from APC data	Number of Rides by Destination											
ROUTE 6A Origin	Cal Poly Kennedy Library	Highland at Mt. Bishop	Highland at Cuesta	Highland at Jeffrey	Patricia at Highland	Patricia at Foothill	Foothill at La Entrada	Ramona at S. Tassajara	Ramona at Palomar	Foothill at Chorro	Casa at Murray	Casa at Deseret (NB)
Cal Poly Kennedy Library - S	-	0	21	2	3	2	0	13	9	2	0	0
Highland at Mt. Bishop	0	-	0	0	0	0	0	0	0	0	0	0
Highland at Cuesta	8	0	-	0	0	0	0	0	0	0	0	0
Highland at Jeffrey	1	0	0	-	0	0	0	0	0	0	0	0
Patricia at Highland	3	0	0	0	-	0	0	0	0	0	0	0
Patricia at Foothill	1	0	0	0	0	-	0	0	0	0	0	0
Foothill at La Entrada	0	0	0	0	0	0	-	0	0	0	0	0
Ramona at S. Tassajara	1	0	0	0	0	0	0	-	0	0	0	0
Ramona at Palomar	7	0	0	0	0	0	0		-	0	0	0
Foothill at Chorro	0	0	0	0	0	0	0	0	0	-	0	0
Casa at Murray	1	0	0	0	0	0	0	0	0	0	-	0
Casa at Deseret (NB)	0	0	0	0	0	0	0	0	0	0	0	-

Thursday, 3/16/17 5:10pm and
5:40pm runs from BlueMAC data Number of Rides by Destination

ROUTE 6A Origin	Cal Poly Kennedy Library	Highland at Mt. Bishop	Highland at Cuesta	Highland at Jeffrey	Patricia at Highland	Patricia at Foothill	Foothill at La Entrada	Ramona at S. Tassajara	Ramona at Palomar	Foothill at Chorro	Casa at Murray	Casa at Deseret (NB)
Cal Poly Kennedy Library - S	-	0	3	0	0	0	0	4	0	0	0	0
Highland at Mt. Bishop	0	-	0	0	0	0	0	0	0	0	0	0
Highland at Cuesta	2	0	-	0	0	0	0	0	0	0	0	0
Highland at Jeffrey	1	0	0	-	0	0	0	0	0	0	0	0
Patricia at Highland	0	0	0	0	-	0	0	0	0	0	0	0
Patricia at Foothill	1	0	0	0	0	-	0	0	0	0	0	0
Foothill at La Entrada	0	0	0	0	0	0	-	0	0	0	0	0
Ramona at S. Tassajara	0	0	0	0	0	0	0	-	0	0	0	0
Ramona at Palomar	2	0	0	0	0	0	0		-	0	0	0
Foothill at Chorro	0	0	0	0	0	0	0	0	0	-	0	0
Casa at Murray	0	0	0	0	0	0	0	0	0	0	-	0
Casa at Deseret (NB)	0	0	0	0	0	0	0	0	0	0	0	-

3/14-16 all day runs from APC	Number of Rides by Destination											
ROUTE 6A Origin	Cal Poly Kennedy Library	Highland at Mt. Bishop	Highland at Cuesta	Highland at Jeffrey	Patricia at Highland	Patricia at Foothill	Foothill at La Entrada	Ramona at S. Tassajara	Ramona at Palomar	Foothill at Chorro	Casa at Murray	Casa at Deseret (NB)
Cal Poly Kennedy Library - S	-	-	537	101	121	150	70	469	218	19	78	3
Highland at Mt. Bishop	0	-	0	0	0	0	0	0	0	0	0	0
Highland at Cuesta	286	0	-	0	0	0	0	0	0	0	0	0
Highland at Jeffrey	66	0	0	-	0	0	0	0	0	0	0	0
Patricia at Highland	106	0	0	0	-	0	0	0	0	0	0	0
Patricia at Foothill	152	0	0	0	0	-	0	0	0	0	0	0
Foothill at La Entrada	52	0	0	0	0	0	-	0	0	0	0	0
Ramona at S. Tassajara	229	0	0	0	0	0	0	-	0	0	0	0
Ramona at Palomar	123	0	0	0	0	0	0		-	0	0	0
Foothill at Chorro	85	0	0	0	0	0	0	0	0	-	0	0
Casa at Murray	282	0	0	0	0	0	0	0	0	0	-	0
Casa at Deseret (NB)	19	0	0	0	0	0	0	0	0	0	0	-

Tuesday, 3/14/17 5:00pm to 11:00pm from APC data	Number of Rides by Destination														
ROUTE 6B Origin	Cal Poly	Grand at McCollum	Grand at Wilson	Mill at Park	Mill at Pepper (WB)	Phillips at Pepper (WB)	Mill at Johnson (WB)	Mill at Santa Rosa (WB)	Downtown Transit Center	Mill at Santa Rosa	Mill at Johnson (EB)	Phillips at Pepper (EB)	Mill at Pepper (EB)	California at Phillips	California at Taft
Cal Poly	-	33	40	11	11	7	12	24	28	0	0	0	0	0	0
Grand at McCollum	0	-	0	0	0	0	0	0	2	0	0	0	0	0	0
Grand at Wilson	0	-	-	0	0	0	0	0	1	0	0	0	0	0	0
Mill at Park	0	-	-	-	0	0	0	0	0	0	0	0	0	0	0
Mill at Pepper (WB)	0	-	-	-	-	0	0	0	1	0	0	0	0	0	0
Phillips at Pepper (WB)	0	-	-	-	-	-	0	0	2	0	0	0	0	0	0
Mill at Johnson (WB)	0	-	-	-	-	-	-	0	0	0	0	0	0	0	0
Mill at Santa Rosa (WB)	0	-	-	-	-	-	-	-	1	0	0	0	0	0	0
Downtown Transit Center	32	-	-	-	-	-	-	-	-	0	0	0	6	2	2
Mill at Santa Rosa (EB)	6	0	0	0	0	0	0	0	0	-	0	0	0	0	0
Mill at Johnson (EB)	5	0	0	0	0	0	0	0	0	0	-	0	0	0	0
Phillips at Pepper (EB)	1	0	0	0	0	0	0	0	0	0	0	-	0	0	0
Mill at Pepper (EB)	1	0	0	0	0	0	0	0	0	0	0	0	-	0	0
California at Phillips	2	0	0	0	0	0	0	0	0	0	0	0	0	-	0
California at Taft	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Thursday, 3/16/17 5:00pm to 11:00pm from APC data

Number of Rides by Destination

ROUTE 6B Origin	Cal Poly	Grand at McCollum	Grand at Wilson	Mill at Park	Mill at Pepper (WB)	Phillips at Pepper (WB)	Mill at Johnson (WB)	Mill at Santa Rosa (WB)	Downtown Transit Center	Santa Rosa (EB)	Mill at Johnson (EB)	Phillips at Pepper (EB)	Mill at Pepper (EB)	California at Phillips	California at Taft
Cal Poly	-	26	67	8	9	3	5	8	94	0	0	0	0	0	0
Grand at McCollum	0	-	0	0	0	0	0	0	1	0	0	0	0	0	0
Grand at Wilson	0	-	-	0	0	0	0	0	4	0	0	0	0	0	0
Mill at Park	0	-	-	-	0	0	0	0	0	0	0	0	0	0	0
Mill at Pepper (WB)	0	-	-	-	-	0	0	0	1	0	0	0	0	0	0
Phillips at Pepper (WB)	0	-	-	-	-	-	0	0	2	0	0	0	0	0	0
Mill at Johnson (WB)	0	-	-	-	-	-	-	0	0	0	0	0	0	0	0
Mill at Santa Rosa (WB)	0	-	-	-	-	-	-	-	6	0	0	0	0	0	0
Downtown Transit Center	103	-	-	-	-	-	-	-	-	25	6	1	1	8	1
Mill at Santa Rosa (EB)	7	0	0	0	0	0	0	0	0	-	0	0	0	0	0
Mill at Johnson (EB)	1	0	0	0	0	0	0	0	0	0	-	0	0	0	0
Phillips at Pepper (EB)	2	0	0	0	0	0	0	0	0	0	0	-	0	0	0
Mill at Pepper (EB)	1	0	0	0	0	0	0	0	0	0	0	0	-	0	0
California at Phillips	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0
California at Taft	3	0	0	0	0	0	0	0	0	0	0	0	0	0	-