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Cross-checking automated passenger counts for ridership analysis

Simon J. Berrebi*, Sanskruti Joshi, Kari E. Watkins

Georgia Institute of Technology, USA

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ABSTRACT

Due to concerns about data quality, Automated Passenger Counting technology has rarely been used to analyze local ridership trends. This paper presents a novel framework to test the consistency and completeness of automated passenger count (APC) data in four cities. Weekday APC data are aggregated at the system level and compared with the National Transit Database between 2012 and 2018. In all four agencies, passenger counts closely follow the fluctuations observed in the national transit database. There is, however, a slight drift in two of the four agencies, possibly due to the diverging trends between weekday and weekend ridership. At the stop-level, missing and duplicate vehicle-trips are identified using schedule data from the General Transit Feed Specification. Missing and duplicate trips only concern a small proportion of stops, which can be eliminated using the proposed method. Overall, this research leads the way towards the analysis of factors affecting ridership on a tight spatial and temporal scale.

Introduction

Even before the start of the COVID-19 pandemic, American cities were experiencing an unprecedented crisis in bus ridership. According to the National Transit Database (NTD), bus ridership has declined every year between 2012 and 2019. While this trend has drawn widespread attention from policymakers and the general public, there still lacks a consensus on its causes and remedies (for a more in-depth review of the literature, see Berrebi et al. (2021). In recent years, several studies have evaluated ridership change over time at the transit agency or regional level (Kain and Liu, 1999; Kohn, 2000; Brown and Thompson, 2008; Lane, 2010; Chen et al., 2011; Iseki and Ali, 2015; Boisjoly et al., 2018; Driscoll et al., 2018; Hall et al., 2018; Graehler et al., 2019; Taylor et al., 2019; Ederer et al., 2019; Watkins et al., 2019; Ko et al., 2019). Other studies have looked at factors explaining static ridership as a cross-section at a more local level (Taylor et al., 2019; Peng et al., 1997; Kimpel et al., 2007; Estupinan and Rodriguez, 2008; Ryan and Frank, 2009; Gutiérrez et al., 2011; Pulugurtha and Agurla, 2012; Dill et al., 2013; Chakrabarti and Giuliano, 2015; Hu et al., 2016; Chakour and Eluru, 2016; Ma et al., 2018; Mucci and Erhardt, 2018). However, the study of ridership trends over time on a hyper-local level remains marginal with only few studies addressing the question (Tang and Thakuriah, 2012; Frei and Mahmassani, 2013; Kerkman et al., 2015; Brakewood et al., 2015; Berrebi and Watkins, 2020). Furthermore, there lacks a framework to test the adequacy of stop-level ridership data to represent ridership trends over time. Transit agencies need to know which segments of their service are most impacted, how ridership responds to service changes, and what micro-phenomena correlate with ridership change. Modeling ridership on a hyper-local level over time is, therefore, necessary to understand the root causes of the decline and identify corrective measures.

Among the data sources that can provide ridership data, Automated Passenger Counts (APC) present a unique opportunity to conduct travel demand analysis on a hyper-local level. Fare collection systems in the United States typically record ridership at the route-level. Rahman et al. (2020) developed a method to split fare-collection ridership data at the stop-level. Nonetheless, the model requires ground-truth data for calibration. There are also methods using WiFi probes to count passengers in vehicles (Ryu et al., 2020; Oliveira et al., 2019). However, these methods are not commercially available at scale to transit agencies. APC trackers, on the other hand, are already widely implemented in bus fleets across the United States. Passenger Counters are laser beacons mounted on transit vehicle doors or treadle mats that record bus ridership at every stop. Each time the laser signal is broken or the mat is stepped on, a passenger boarding or alighting is detected, depending on the direction of the motion. APC technology is designed to record the precise geolocation of passenger activity, which provides the necessary stop-level granularity for in-depth ridership analysis.

Although transit agencies started deploying APCs in the mid-1970′s (Attanucci and Vozzolo, 1983), the technology has seldom been used to

* Corresponding author.
E-mail address: SIMON@BERREBI.NET (SJ. Berrebi).

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explain disaggregated ridership change. In 2006, a TCRP Synthesis on Fixed-Route Transit Ridership Forecasting and Service Planning Methods surveyed transit agencies on the state of practice (Boyle, 2006). The study found that APC was the least likely data source to be used for ridership forecasting and, according to respondents, the technological advancement most likely to change forecasting methodology. In 2008, a TCRP Synthesis on Passenger Counting Systems found that "It is still the rule rather than the exception to install APCs on only a portion of the bus fleet and then rotate the APC buses among the various routes" (Boyle, 2008). Today, many transit agencies approach or even meet full APC coverage, which could enable the analysis of ridership on a highly specific spatial and temporal scale. The question remains, however, whether the consistency and completeness of APC data are sufficient to be relied upon for multi-year network analysis.

To enable the understanding of system-wide and even national ridership trends, automated passenger count data must be consistent with these trends. Passenger count data can only be useful if they match the monthly unlinked passenger trip from NTD on aggregate, which are typically derived from manual counts. Otherwise, if the two data sources show diverging trends, then either APC or NTD may be at fault. But if both data sources are consistent, then they are most likely both accurate. To ensure the consistency of APC data, this study compares aggregated APC trends with NTD.

In order to enable deep dives across bus stops and times of day, there needs to be at least some data collected at all stop-trip combinations. If, during an entire mark-up period, no data is collected on a scheduled trip at a particular stop, then APC data will be missing an unknown number of passenger boardings and alightings. Analyzing these data as if they represented overall ridership could lead to a survivorship bias. Over time, as older vehicles on the fleet get replaced with newer ones that are equipped with APC, the decline in missing trips could be interpreted as an increase in ridership. Verifying whether every scheduled trip is sampled at least once at each stop during the mark-up ensures that ridership trends can be evaluated on the basis of complete data sets. This study presents a novel methodology to cross-check APC data completeness with the General Transit Feed Specification (GTFS), a data standard for schedules, routes, and stops.

This paper is informed by interviews of practitioners and subject matter experts. The research team spoke with transit officials responsible for collecting, analyzing, and managing APC data at the four agencies in our case-study. Emails were exchanged with Federal Transit Administration officials responsible for National Transit Database reporting. Finally, representatives from the leading APC hardware and software companies were interviewed.

In this paper, the consistency and coverage of APC data between 2012 and 2018 are evaluated in four transit agencies, TriMet, OR, Miami-Dade County, FL, Metro Transit, MN, and the Metropolitan Atlanta Rapid Transit Authority (MARTA), GA. The next section presents the main studies from the literature on the accuracy of APC data. Next is a description of the data, case studies, and methodology, which could be replicated on any type of APC capturing the number of boarding and alighting passengers. The Results section describes how the automatically collected data perform in each of the four transit agencies over time. Finally, broader implications and future work are discussed in the conclusion.

Review of practice and literature

The research on APC data thus far has focused on assessing the accuracy of counts themselves. Since the early 1990s, studies have cross-checked the data with manual counts, fare collection, and videocameras (Boyle, 2008). In 1991, Strathman and Hopper compared APC with manual counts in TriMet buses (Strathman and Hopper, 1991). They did not find any significant under or over counting of passenger boardings. In 2003, Kimpel et al. compared APC data with counts derived from video cameras (Kimpel et al., 2003). The study found that, overall, passenger boardings recorded by APC were consistent with video camera counts. The post-processing of APC data was found to be sufficient to ensure accurate passenger counts.

The Federal Transit Administration mandates that transit agencies relying on APC for NTD reporting must benchmark the data with manual counts in the first year and periodically thereafter (NTD, 2018). These steps ensure that APC data are consistent with manual counts on individual trips. The benchmarking requirement is typically targeted at passenger loads, which are more sensitive to errors than unlinked passenger trips; both are included. The consistency between manual and automated counts is tested on a relatively small subset of the bus network and on a single time period. Transit agencies that rely on manual counts for NTD reporting can pick a random sample of vehicle-blocks to estimate system-wide ridership (Chu, 2010). For transit agencies looking to change methods of data collection, testing the consistency can help identify any bias that would have caused historical data to differ from what was reported to NTD.

Interviews with researchers and practitioners reveal that all passenger count data sources have potential flaws. In crowded conditions, surveyors conducting manual counts can lose track of passenger boardings and alightings. Fare collection systems are unable to directly account for fare evaders. Therefore, in the absence of significant differences between automated passenger counts and other datasets, these types of studies only provide limited intelligence on the quality of APC data.

The usefulness of APC ultimately depends on the coverage and sampling plan. Siebert and Ellenberger recently developed a new statistical tool to allocate APC-equipped vehicles throughout the network (Siebert and Ellenberger, 2019). The sampling plan is designed to meet NTD criteria with a fleet only partially equipped with APC. Unlike NTD reporting, the analysis of hyper-local ridership trends cannot rely on partial sampling. In order to assess the state of practice, APC data need to be evaluated at every stop and trip. The literature, therefore, currently lacks an evaluation of the consistency and completeness of APC data, which is the focus of this paper. Transit agencies can easily check how their APC data compares to the four case studies presented in this study. By testing these criteria, this research clears an important hurdle towards the application of APC data for ridership modeling.

Methodology

Consistency

In order to verify whether hyper-local ridership trends were consistent with NTD, APC data were aggregated at the system level. We took the sum of weekday average ridership per mark-up over all stop-route-direction combinations. While NTD contains the number of monthly unlinked passenger trips, APC data is averaged by day at the trip level. To avoid the temporal mismatch, we simply normalized both datasets to the first mark-up for which APC data were available. We then took a four-month rolling average of the normalized NTD data to match the mark-up periods in APC. Through this methodology, we only test APC data from weekdays, but Saturdays and Sundays could be tested in the same manner.

This methodology allows to identify systematic biases, which may increase or decrease in intensity over time. If, for example, the fleet has heterogeneous APC trackers, which are all calibrated differently, then as new vehicles get on-boarded and old vehicles get decommissioned, there could be a spurious trend, upward or downward. Another example is if the under-counting is caused by missing trips, which could change over time as the coverage increases or the discarded measurements decrease. Comparing APC with NTD allows to identify these issues. At the same time, it is also possible that any deviation between APC and NTD be caused by differences in weekday versus weekend ridership trends.

Completeness

In order to verify the complete sampling of scheduled trips in APC, the number of trips was compared with GTFS at each stop-route combination. Some of the agencies in the case study assign no unique trip identifier in APC, which makes a one-to-one correspondence at the trip-level impossible to establish. Instead, we counted the number of trips for which APC data were collected at least once during each markup. To determine the number of scheduled trips in GTFS, the stop_times and trips tables were joined using the trip_id field for each stop-route-direction. Histograms of the difference between APC and GTFS trips over successive years can then show how the number missing and duplicate trips has changed over time.

This methodology allows to quantify the number of stop-route-directions with missing trips. A scheduled trip is missing from APC if it was not sampled even once during the markup. It also helps to identify locations where the same trip was recorded multiple times by mistake. As the APC coverage and accuracy improves, missing and duplicate trips become rarer. It is therefore important to distinguish between real ridership trends and the artifacts resulting from technological issues.

Although transit agencies in our case study all have full or close-to-full APC coverage, the hardware is subject to daily use and therefore prone to defect. Many of the measurements produced by functional APC units are discarded in the post-processing phase. For example, TriMet reported discarding 25% of recorded passenger activity. In an evaluation of TriMet APC, Strathman and Hopper tested sampling plans and found that data recovery rate was spatially correlated with garage depot, block assignment, and other related factors (Strathman and Hopper, 1991). Although vehicles were deliberately dispatched across the system, some routes were ultimately under-represented in the sample. For the application of modeling hyper-local ridership trends, identifying potential sources of bias that may affect particular locations and have drifting effects over time is paramount.

Case studies

To evaluate the relationship between transit ridership and frequency, four transit agencies were selected based on the quality of their APC data. The research team initially contacted 14 mid-sized transit agencies. Of these agencies, eight were able to provide stop-level data. Three of these data sets did not pass our initial screening. One agency had undergone a network redesign, which created disruptions of a greater magnitude than the phenomena we were looking to capture. The analysis presented in this paper is therefore based on four agencies, which are at the leading edge of best practices:

- Tri-County Metropolitan Transportation District of Oregon (TriMet) in Portland, OR
- Miami-Dade Transit in Miami, FL
- Metro Transit in Minneapolis/St-Paul, MN
- Metropolitan Atlanta Rapid Transit Authority (MARTA) in Atlanta, GA

Although they come from widely different regions of the United States, the four agencies have similar governing structures. They are all multi-county authorities with an independent board from their states and local municipalities. The agencies are also similar in size: in 2018, they all operated between 51 and 57 million unlinked passenger trips. Finally, these agencies have a history of early technological adoption, which made the analysis of APC data over time possible.

The Tri-County Transportation District of Oregon (TriMet) is the largest transit agency operating in the Portland Metropolitan Area. TriMet operated bus service at 6800 distinct bus stop in 2017. In addition to bus service, the transit agency also operated light-rail and commuter rail. TriMet was one of the pioneers when it started rolling out APC technology in 1985 (Boyle, 1998). TriMet has developed its own software to match APC data with the corresponding stop and block. The agency also cleans and filters APC data itself. The bus fleet has been fully equipped with APC since 2014. About 25% of recorded data are discarded in post-processing.

Metro Transit operates bus and rail transit service in the seven-county Minneapolis/St-Paul Metropolitan Area. The Metro Transit bus networks included 13,400 distinct bus stops in 2017. The transit agency operates local and express bus service in addition to Bus Rapid Transit, light-rail, and commuter-rail. Like TriMet, Metro Transit also developed post-processing software in-house. In 2008, Metro Transit equipped the first 10% of its buses with passenger counting technology. In ten years, APC coverage has grown to 95%. The passenger counting devices come from Trapeze and Red Pine, which was acquired by Trapeze.

The Metropolitan Atlanta Rapid Transit Authority (MARTA) operates bus and rail service in the Atlanta Region. In 2017, MARTA operated bus service at 9400 bus stops forming a feeder system around the heavy rail network. The transit agency uses the Ride Check Plus post-processing tool provided by Clever Devices. The APC hardware were provided by IRMA. Since 2010, the bus fleet is fully covered by APC units. However, according to interviews with planning staff, defective hardware and discarded data substantially reduce the actual coverage.

Miami-Dade Transit is the transit authority responsible for providing service in the Miami Region. In 2017, Miami-Dade transit provided service at 8100 bus stops in addition to the heavy-rail and mono-rail systems. Buses are equipped with APC trackers from Urban Transportation Associates. The same company provides software to clean, process, and maintain the data. Miami-Dade has had 100% APC coverage since 2008. However, over this period of time, the agency has subcontracted service to third party operators, which are not equipped with APC systems.

Data

For each case study, the research team asked service planners to provide APC data averaged by trip and by stop-route-direction for each mark-up going back as far as possible. While the exact format of the data differed slightly between agency, each data-set contained the average number of passenger boardings and alightings for each trip during each mark-up (for more information about the data, see Berrebi and Watkins (2020). While some agencies were able to provide the sample size on which these averages were based, others did not have the information available. Since transit agencies started nearing full APC coverage at different times, the timespan of available data is different for each. We aggregated weekday ridership and frequency data over the entire system by mark-up to evaluate APC data completeness and consistency as of 2012 and going as close as possible to the present. Data were available from 2012 to 2017 at TriMet and Metro Transit, from 2013 to 2017 at Miami-Dade, and from 2014 to 2018 at MARTA.

At the end of each day, when transit vehicles return to the maintenance facility, APC data are uploaded onto a server. From there, an initial filtering process removes compromised data. For example, any trip (i.e. vehicle run taking place every day on the same route at the same time) with a large difference in the total number of boardings and alightings is discarded (Furth et al., 2005). This step is based on the assumption that all alighting passengers must have boarded at some point and vice versa. Another example is the elimination of passenger activity recorded too far from the actual stop. Based on a survey of transit agencies, TCRP Synthesis Report 77 describes the typical steps involved in the process (Boyle, 2008). Some agencies use proprietary data-processing software, making it impossible to compare data cleaning rules for each agency. Nonetheless, we expect these steps to be consistent across agencies based on interviews with practitioners.

Transit planners typically publish GTFS data at the beginning of each mark-up period. The schedule information provided by the GTFS files is updated throughout the mark-up as slight changes in schedules and routes are planned. TriMet was the first agency to publish service information in the GTFS standard. In 2007, they partnered with Google to define the standard, which has been adopted by transit agencies across the world since (McHugh, 2013). In this study, historical GTFS data were obtained from the third-party repositories OpenMobilityData and GTFS Data Exchange. The first GTFS files published following the beginning of each mark-up were selected. The number of daily trips in each stop-route-direction combination was counted in both GTFS and APC. For a more in-depth description of this process, please refer to Joshi (2019).

Since 1974, transit agencies are responsible for reporting financial and service information to the National Transit Database. The Federal Transit Administration (FTA) uses NTD data to allocate funding. The data are openly accessible and include unlinked passenger trips by month. Although the FTA allows the use of APC for NTD reporting, the criteria are prohibitive for most agencies. For this reason, no agency in our case study relies on APC data to report unlinked passenger trip information. Miami-Dade uses manual counts and all other agencies use the fare collection system. This enables a comparison between fare collection or manual data and APC for each agency using NTD.

Results

Consistency

Fig. 1 shows normalized NTD (blue) and APC (red) unlinked passenger trips. In all four agencies, the two data sources are consistent with each other in representing ridership fluctuations. Sudden jumps and dips in unlinked passenger trips happen at about the same time, besides the obvious lag introduced by the rolling-average. These system-wide changes in ridership include both seasonality and other short-term trends affecting ridership.

Fig. 1 shows whether long-term ridership trends in weekday APC are consistent with overall NTD. Ridership trends are clearly consistent in Portland and Atlanta. In both agencies, the red line follows the blue line throughout the entire time span for which data are available. There are no prolonged time periods during which APC is systematically higher or lower than NTD. In Miami and Minneapolis, on the other hand, APC data seems to be slightly more optimistic about the change in ridership over time than NTD. In both agencies, the red (APC) lines show a slower decline in unlinked passenger trips than NTD. In the last four years, APC estimates in Miami and Minneapolis are consistently higher than NTD.

The fact that automated passenger counts can capture the fluctuations impacting ridership on a system-wide level suggests they should also be reliable for modeling short-term change on a local level. The data can also be used to model longer-term trends in Portland and Atlanta. In Miami and Minneapolis, the upward drift in ridership could be due to a number of different factors. Firstly, this study is limited to weekday ridership. We know from a separate analysis that ridership has been declining at a faster rate, especially in Miami and Minneapolis. Another possible explanation is the increasing APC quality. On one hand, a greater proportion of the fleet may be equipped with APC. On the other hand, evolving software could be reducing the occurrence of under-counting through a process of internal checks and validations. The next section evaluates the completeness of APC data over time.

Completeness

Fig. 2 shows a histogram of the absolute difference in daily trips between GTFS and APC. Since the timespan of APC availability varies by agency in our case study, the comparison is made between the first year (2012 for TriMet and Metro Transit, 2013 for Miami-Dade, and 2014 for MARTA) and the last year (2018 for MARTA, 2017 for all other agencies). All agencies have varying proportions of trips in GTFS missing from APC, and vice versa. In order to discern the differences between APC and GTFS, the 79–99% of stop-route combinations that have the same number of daily trips are shown as a truncated dashed line. The proportion of stop-route combinations with complete sampling (i.e. same number of trips in APC and GTFS) are shown in Table 1.

Overall, the vast majority of stop-route combinations have the same number of trips in APC and GTFS in both the first and the last year.

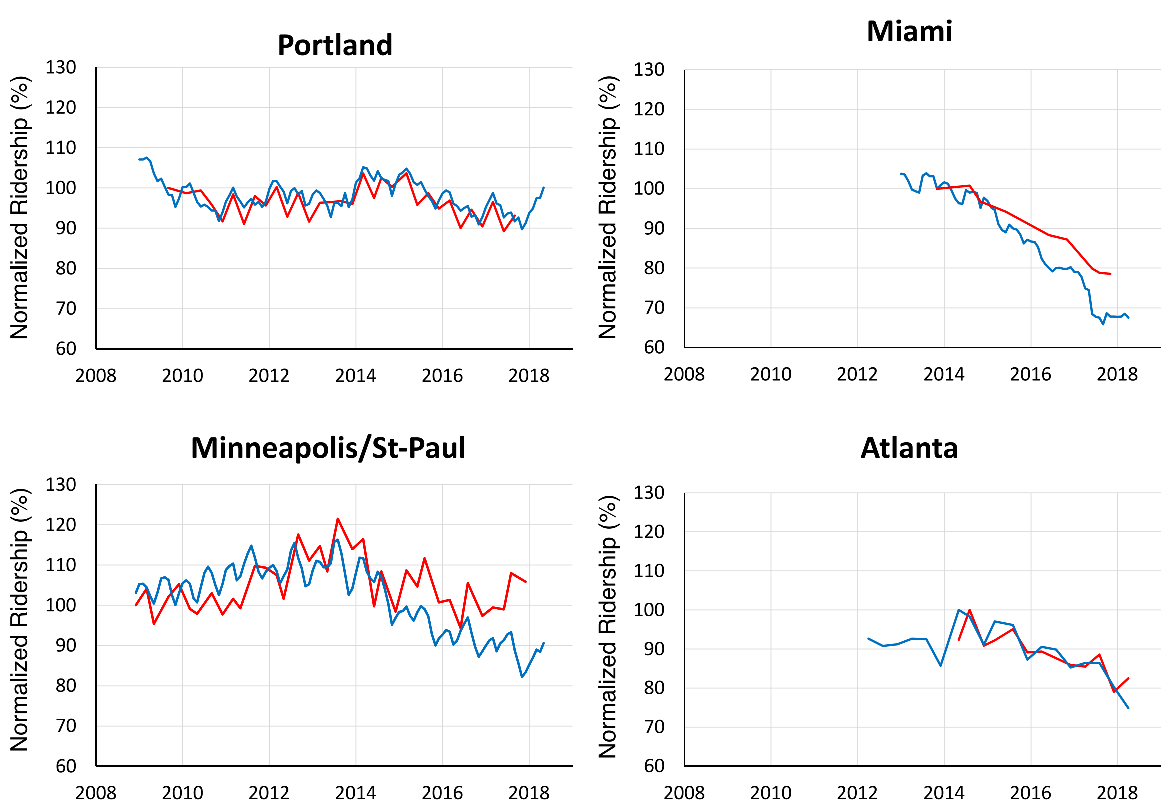

Fig. 1. Comparison of system-wide NTD (blue) and APC (red) unlinked passenger trips.

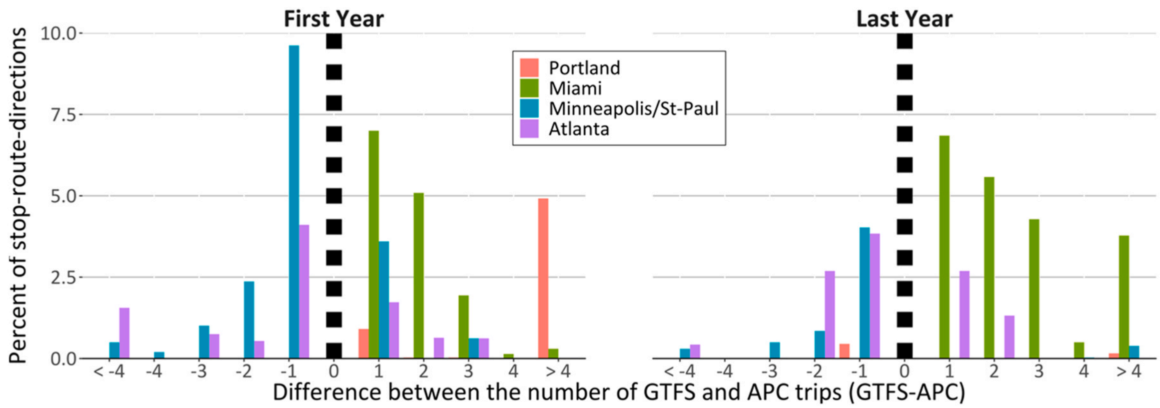

Fig. 2. Histogram of the difference between GTFS and APC trips (GTFS-APC) in the first and last year.

Table 1
Percent of stop-route combinations with full sampling (i.e. same number of trips in APC and GTFS).

	First Year	Last Year
Portland (2012–2017)	93.4	99.4
Miami (2013–2017)	85.5	79.0
Minneapolis/St-Paul (2012–2017)	82.1	93.9
Atlanta (2014–2018)	90.0	89.0

TriMet's APC data is quite complete with only 6% of stop-routes missing trips in 2012 and close to none in 2017. In Miami, the proportion of stop-routes with missing trips increased by 7% between 2013 and 2017. This could be due to the increase in subcontracting during that period, which led to the loss of APC data. Subcontracted service in Miami is performed on third-party vehicles, which are not equipped with APC. In Minneapolis/St-Paul, the proportion of stop-routes with the same number of trips in APC as in GTFS increased by 12% between 2012 and 2017. In particular, the proportion of stop-routes with more trips in GTFS than in APC was virtually null in 2017. This could be one of the reasons or the drift observed in APC data in the last section. Finally, the proportion of missing and duplicate trips in Atlanta remained constant between 2014 and 2018.

The sizable portion of stop-route combinations with missing or duplicate trips suggests that some measures should be taken to avoid the associated bias. It is usually preferable to remove stop-routes with incomplete data than to let the APC sampling dictate the direction of ridership change at those locations. The process employed to compare APC and GTFS can also be used to define a subset of stop-routes with the same number of trips in APC and GTFS.

Conclusion

Overall, automated passenger counts are sufficiently consistent and complete to support the analysis of ridership trends on a hyper-local level. In all four agencies, aggregated APC data at the system-level follow the short-term fluctuations exhibited in NTD data. While there was a slight upward drift in Miami and Minneapolis, these trends correspond to the deviation between weekday and weekend data, which are not represented in the APC dataset used in this paper. Missing and duplicate trips remain by-and large a limited phenomenon that only affects less than 20% of stop-routes in the worst case. Nonetheless, stop-route combinations with missing or duplicate trips should be meticulously eliminated from the analysis. These trips can create spurious trends in ridership when, for example, what appears to be an increase in ridership may only be a decline in missing trips.

The completeness test enables transit agencies to identify and target the causes of missing and duplicate trips. If data are missing on a route across stops and trips, then cause may be found in the maintenance garage where vehicles are stored overnight. If data are missing on an entire route but for only a specific trip, then the tracking device on the bus scheduled to operate this trip is probably responsible. If data are missing at a particular stop across routes and trips, then a faulty GPS connection at that location may be the problem. Duplicate trips are typically the result of service changes occurring during a mark-up. The test of completeness can be used to target these instances and collate the multiple versions of GTFS.

This paper introduced a new methodology to assess the consistency and completeness of APC. This assessment is the first step towards new planning and analysis applications of the data. According to the Transit Capacity and Quality of Service Manual, potential applications include ridership estimation, bus stop relocation, dwell time estimation in scheduling, and ridership elasticity to frequency (Kittelson and Associates, 2013). Estimating the impact of service decisions on ridership requires a reliable passenger counting system. This is why the establishment of tests and metrics are so important.

Passenger counts can also be available from fare collection systems. Transit agencies in the United States typically rely on legacy farebox systems that are not linked with GPS, and can, therefore, only provide data at the route-level. However, recent trends in AFC show a promise for passenger-counting at the stop-level. Some transit agencies, including Sound Transit in Washington, have access to disaggregated passenger count data through smart-card systems. Abroad, transit agencies in Seoul, Korea and Sydney, Australia even have access to disaggregated vehicle occupancy information in real-time. While AFC has its own imperfection, due for example, to fare evasion, it has the potential to be a reliable alternative to APC. Future research should compare the two passenger-counting technologies.

As transit agencies gain in data collection capabilities, setting up a scalable and consistent framework is important. Although APC technology was hailed as a potential solution to the labor-intensive manual counts when they were first introduced fifty years ago, they are still not used at their maximum potential. In September 2017, a new data standard called "GTFS-ride" was released to enable real-time feeds of passenger count data (Carleton et al., 2019). As transit agencies start to attain high APC coverage and implement new fare collection systems, which can track vehicle location, GTFS-ride provides the opportunity to make the data available in a standard format. Greater integration across data sources, applications, and institutions could lead to further benefits for automatically collected data.

Real-time APC could eventually inform vehicle arrival predictions (Shalaby and Farhan, 2004; Patnaik et al., 2004) and real-time control (Berrebi et al., 2015, 2018a, 2018b). The dissemination of real-time passenger counts still faces numerous challenges, including the necessity to rely on raw counts without going through post-processing. If APC data is to inform travel decisions for both passengers and operators, the level of accuracy must be measured against other, more established, data sources. Future research should therefore develop tests of APC data quality specifically adapted for real-time applications.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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