GETTING MORE OUT OF DATA IN PUBLIC TRANSIT

by

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STATEMENT OF DISSERTATION APPROVAL

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ABSTRACT

Recent years' advancements in sensing technology have generated an enormous amount of data in various fields and industries, including transportation. Public transportation systems, as a critical component within the transportation ecosystem, have also been experiencing much data growth. The availability of big data not only improves traditional transit service monitoring, but also enables high-resolution transit performance analysis that guides decision making. However, the potential of these datasets is not fully explored yet due to several challenges such as residing noises in data records and limited computational power. This dissertation tries to address three of those challenges: how to incorporate and analyze missing data due to lack of electronic footage, how to enable high-resolution performance measurements that require extensive computation, and how to interpret the high-resolution results?

The first challenge was addressed in a quest to find missing data on the different fare payment methods without electronic footage, and their impact (among other factors) on bus Dwell Time (DT). Integrating information from multiple data sources, a combined approach of optimization and regression analysis was developed that offers a data-driven evaluation of existing fare payment structures and their individual effects on DT. Using the 35M bus rapid transit line operated by the Utah Transit Authority as a case study, the method demonstrates the robustness and strong predictive power in DT modeling. Then we introduce a new algorithm that is computationally elegant and mathematically

efficient to address the second challenge of run-time reduction. An open-source toolbox written in C++ is developed to implement the algorithm. The toolbox is tested on the City of St. George's transit network to showcase dynamic transit accessibility analysis. The experimental evidence shows significant reduction on computational time. To address challenge three on interpreting the high-resolution transit accessibility results, the algorithm in the previous study was applied to the Salt Lake City's network to compute travel times at multiple departure times throughout the day. A series of indicators that are intuitive to interpret were developed to determine the varying causes of poor transit accessibility and identify areas with immediate needs for service improvements.

This dissertation manifested that utilizing newly available datasets not only improves the resolution and accuracy of the transit service assessments, but also takes a step further to enable a comprehensive study of various factors (stop characteristics) impacting transit service efficiency and quantifying critical decision-making indices unveiling transit service effectiveness that were not possible before. Findings from this research are expected to lead to methodological advancements in data-driven approaches in public transit studies, and help transform the transit management mindset into a model of data-driven, sensing, and smart urban systems.

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CHAPTER 1

INTRODUCTION

In the United States, public transit trips have increased by 34 percent since 1995 (*1*). The magnitude of transit trips growth can be better understood when compared to the population growth of approximately 21 percent within the same period. In 2016, Americans took 10.4 billion trips via public transit services operated by more than 6,800 transit agencies employing more than 400,000 people (*1*). Public transit is a fundamental component of the transportation system that plays a key role in addressing challenges faced by modernized society, with the most important being congestion. Congestion causes extensive economic burden on society. Schrank et al. (*2*) estimated a congestion cost of $121 billion in urban areas of the United States alone. They determined that congestion cost would rise to $142 billion (17% more) without public transit. The benefits of public transit is multifaceted, other than congestion relief. Economic, health, energy, accessibility, and environmental challenges can also be remedied by public transit services, which are explained in more detail as follows.

Public transit enables economic growth by creating direct and indirect jobs, encouraging land use development, reducing congestion costs, increasing labor income, and increasing business sales and tax revenue (*3*-*5*). Public transit also helps families to save money by providing an affordable transportation option. Beirão and Cabral (*6*) have studied travelers' attitudes towards public transit and reported that even car users acknowledge public transit as cheaper option. APTA (*1*) reported a two-person household can save about $10,000 a year by downsizing to one car.

Various common health problems in modern society such as heart disease, obesity, and depression are associated with inadequate physical activity (*7*). Encouraging an inactive population to use public transit increases their daily walking-time to reach the recommended level of daily physical activity (*8*), and consequently, improves public health (*9*-*11*).

The public transit fleet, as an integral part of the transport and mobility industry, plays an important role on the energy consumption and environmental profile of cities (*12*). The modal shift from private car to public transit decreases auto travel and consequently results in reduction of vehicle-mile-traveled, fuel consumption, and emissions. Schrank et al. (*2*) reported public transit use in 2011 saved 450 million gallons of fuel in the United States. In addition, public transit use saves 37 million metric tons of carbon emissions annually (*1*).

Access to public transit provides mobility options and enables disadvantaged populations to perform the necessary daily activities such as commuting, visiting doctors, and participating in social activities (*13*). On the other hand, poor access to public transit can cause social exclusion and limit the available opportunities for disadvantaged populations (*14*).

As mentioned above, public transit offers various benefits and is a crucial part of solutions towards sustainable economic performance, social welfare, and environmental resilience. The benefits of public transit proliferate as transit ridership increases. Public transit ridership is influenced by many factors such as socio-economic factors (*15*), transit fare (*16*), service coverage (*17*), and travel time (*18-19*). Travel time is one of the critical factors reflecting the feasibility and attractiveness of transit use (*20*), which itself consists of four main components: ingress/egress time, time spent at stops, time spent between stops, and time spent for transfer. Therefore, understanding the nature of factors impacting each component of transit travel time helps transit authorities with planning and operating their transit network more effectively in order to increase ridership.

In recent years, advancement in sensing technologies and data management enabled public transit agencies to collect a large amount of data in a consistent format. The availability of such data sources empowers researchers to conduct high-resolution studies on travel time (among other factors) that lead to better understanding of the transit operation. This field is still in its infancy and various challenges are present in working with automatically collected data and high-resolution analysis. This research aims to address some of these challenges and provide a better understanding of transit operations in order to improve transit service efficiency and effectiveness.

1.1 Problem Statement

Public transit agencies and researchers have traditionally relied on manually collected data and/or simplified forms of data for planning and evaluating transit services (*21-22*). Manual data collection is labor-intensive and time-consuming. As a result, project budgets and time constraints limit the sample sizes and generality of models (*23*). In addition, the unavailability and inconsistency of data formats forced researchers and practitioners to use simplified forms of transit networks (*20*). Consequently, the performance measures (such as travel time) were estimated rather than calculated (*21*).

In recent years, there has been growing adoption and utilization of various sensing technologies by transit agencies to collect and share data. Big data analytics in public transit allow high-resolution transit service analysis that not only provides real-time information to riders, but also guides investments and decision making for service optimization. However, the potential of these datasets is not fully unveiled due to several challenges such as noise residing within data records and limited computational power. This dissertation aims to address some of these challenges in two applications:

1) Fare payment structure and Dwell Time (DT) modeling;
2) Public Transit Accessibility (PTA) and transit gap causality analysis.

In the first application, Automatic Vehicle Location (AVL), Automatic Passenger Count (APC), and Automatic Fare Count (AFC) datasets were used to analyze the impact of various factors such as fare payment structure on transit DT. Even though these datasets provide a massive amount of information, each has downsides of its own in terms of accuracy, format, and fragmented information that prevent their mutual integration. This forced previous studies on fare payment structure and DT analysis to either rely on manually collected data or ignore these issues, which led to biased results.

In the second application, network-level public transit data must be jointly used with census data to measure PTA and transit gap. The General Transit Feed Specification (GTFS) is an emerging dataset nowadays that offers a unified format of network-level transit information (e.g., schedule, trips, stops, and routes). It can be used to compute travel time from one station to another, which is required information for PTA. However, implementing such an analysis requires extensive computational power utilizing readily available software (e.g., Esri's ArcMap Network Analyst). Moreover, the high-resolution results are too complicated to interpret using traditional methods due to the added temporal dimension.

The specific challenges and limitations regarding each application are described in detail in Sections 1.1.1 and 1.1.2.

1.1.1 Fare payment structure and dwell time modeling. Transit service reliability and efficiency are influenced by the variability in bus operating time. Such variability will affect headways, which may lead to bus-bunching and inconsistent wait times for riders. DT, or the time spent at stops, is a major component of bus operating time (*24*-*26*). Therefore, understanding the nature of factors influencing DT will assist transit authorities with planning and operating their bus systems more effectively.

There are a number of factors impacting DT such as passenger demand, fare payment methods, vehicle configuration, passenger load, door usage, and platform configuration (*27*). Previous studies have reported that fare payment structure can have significant impact on passenger boarding/alighting time and consequently on bus DT. To analyze such an impact, the classic linear regression model with ordinary least square has been widely used to model bus DT. Traditional DT modeling relies on manually collected data (*28*-*32*) and suffers from a limited number of samples, leading to loss of generality.

The APC, AFC, and AVL datasets have gained popularity in recent years for DT modeling as they complement each other and provide a massive amount of information in a cost-effective way (*23, 33*-*34*). However, the following challenges must be addressed to enable the use of these datasets and ensure the reliability of DT modeling and fare payment structure results: (1) how to screen-out noises in the datasets? Past studies have used simple filtering threshold while ignoring the fact that the noises can be small enough to sift through filtration; (2) how to categorize behavior-controlled DT observations? The first step in modeling simultaneous boarding and alighting is to categorize observation based on the behavior (e.g. boarding) that controls DT. However, past studies, that used automatically collected data, have ignored such simultaneous passenger behavior; and (3) how to analyze impact of transactions that do not have electronic footage on DT? The fare payment methods with no electronic footage were assumed to have identical effect on DT which is an oversimplified assumption leading to over/underestimation of their impact.

1.1.2 Public transit accessibility and transit gap causality analysis. PTA refers to the ability to reach goods, services, and activities via public transit. PTA is an important factor that influences users' mode choice. Good PTA encourages users to use public transit and active transportation. Consequently, it increases transit ridership, improves public health, and enhances the urban environment (*9*, *35*). An accurate assessment of PTA enables transit agencies to identify areas in most need of improvement and guide investment decisions and land use development (*36*).

Prior to 2005, PTA measures have either excluded travel time or used an estimation of travel time based on simplified transit network data. However, overlooking travel time tends to overestimate the portion of the population with transit access (*20*). GTFS, introduced in 2005, provides a detailed schedule of transit network in a uniform data-format. Since 2005, many PTA studies have used GTFS to measure travel time for a specific time-of-day (e.g., peak hour) (*37-40*). This often leads to an overly optimistic evaluation of PTA as the optimum transit service is provided at peak hour and the temporal fluctuation of transit service is ignored. To address this problem, PTA can be measured for several times-of-day (dynamic PTA) (*41*-*42*). The measured PTA (supply) can be compared to the need for transit services (demand) to identify transit gaps (mismatches) and guide transit investment decisions (*42*-*43*).

The current state of PTA and transit gap analysis faces three main challenges that have not been addressed yet: (1) Calculation of travel time for several times-of-day is a computational-extensive and time-consuming process that undermines its feasibility. For example, Farber et al. (*42*) reported that the calculation of travel time between all transit stations for every minute of the day for the Salt Lake City transit network with 1,400 stations, and 100 transit routes would take approximately 60 days on a quad-core machine in ArcGIS. (2) Analyzing and interpreting dynamic PTA results remains challenging due to the complexity of the added temporal dimension. Headways, standard deviations, coefficients of variation, ranges, and Fourier transforms can all be used to measure the temporal variability of transit services. However, little has been done in justifying the use of these methods or comparing their results. (3) No study to date has successfully identified the underlying reasons for poor PTA. PTA is influenced by the efficiency of the transit service and/or geographic location of the subject area. Poor PTA caused by inadequate transit services can be remedied by the transit agency via investment. However, poor PTA caused by geographical disadvantage (i.e., long distance between origin and desired destinations) requires land development efforts. Therefore, it is critical to distinguish between these two causes of poor PTA in an effort to make informed decisions.

1.2 Research Objectives

The main goal of this research was to develop innovative methodological frameworks for data-driven high-resolution analysis from newly available datasets in public transit to guide and refine the decision-making process. The defined research goal was developed through seven major objectives that align with the previously explained research problem statement. These major research objectives regarding each application were described in Sections 1.2.1 and 1.2.2.

1.2.1 Fare payment structure and dwell time modeling.

The fare payment structure and DT modeling research objectives were defined as follows:

1) Identify various noise types (e.g., noises caused by device malfunction) that may exist in the APC and AFC datasets and develop effective filtration methods;
2) Develop a methodological framework for categorizing the behavior-controlled DT observations into boarding-controlled, alighting-controlled, and atypical observations;
3) Devise a procedural method to estimate the number of users utilizing each non-electronic fare payment method (e.g., cash payers and prepaid pass holders) in each observation and validate the results through statistical testing. This is to model the impact of different fare payment methods on DT using APC and AFC datasets.

Following these objectives, the 35M MAX Bus Rapid Transit (BRT) line in Utah Transit Authority's (UTA) network was selected for DT analysis. To model DT and the fare payment structure quantitatively, APC and AFC records were collected for May 2014. The APC and AFC datasets were postprocessed and matched. Three sources of noises in the data were identified and screened out: (1) abnormal results in matching datasets (e.g., number of passengers boarding/alighting using electronic fare payment method in AFC record is bigger than total number of passengers boarding/alighting in APC records); (2) device malfunction (e.g., 10 passengers board in 1 second); and (3) unusual events leading to erroneous data records (e.g., a passenger that boards and alights multiple times in one stop or a passenger blocks APC device infrared light).

The 35M MAX BRT line allows simultaneous boarding and alighting, so the next step was to use a cleaned dataset for categorizing behavior-controlled DT observations. For this purpose, atypical activity observations were screened out according to 10 seconds per passenger boarding/alighting time threshold. The threshold was selected based on previous studies' results and field observation. Genetic Algorithm (GA) was used to minimize the error of two separate objective functions for boarding-controlled and alighting-controlled DT calculation, with constraints selected based on previous studies' results and field observations. A DT observation was controlled by boarding (alighting) activity if the boarding-controlled (alighting-controlled) function's error was smaller than the alighting-controlled (boarding-controlled) function's error.

Finally, optimization technique and regression modeling were combined in a procedural method to estimate the influence of each fare payment method (among other factors) on DT. In this procedural method, regression modeling was applied and the impact of contributing factors (such as electronic fare payment) on DT were estimated. This regression model doesn't incorporate each nonelectronic fare payment method (e.g., cash transactions) individually as they are not recorded separately. In other words, the sum of (aggregated) number of passengers using nonelectronic fare payment methods is incorporated in the model as one variable. In the next step, GA is used to estimate each missing variable (i.e., nonelectronic fare payment methods) in every observation. The GA model is built based on the assumption that the sole difference between the aforementioned and perfect (where $R^2 = 1$) regression models is caused by using the nonelectronic fare payments methods as one aggregated variable (in aforementioned regression model) versus separate variables (in perfect regression model). Then the estimated disaggregated missing variables were used in the regression model to estimate their impact on DT. Three posterior statistical tests were conducted to validate the results including a seemingly unrelated estimation test to assess the consistency of parameter estimates of the common variables in two aforementioned regression models (i.e., one with aggregated and one with disaggregated variables of nonelectronic fare payment methods), a matching test to ensure model estimation power by comparing the estimated missing variables with their actual observed values (collected manually), and an estimation bias test to check the magnitude of possible bias in parameter estimates.

This approach resulted in the ability to screen out noises, develop high-accuracy regression models based on categorized behavior-controlled DT observations, and incorporate missing variables such as nonelectronic fare payment methods in DT modeling solely using APC and AFC datasets, while exploring the influence of various factors on DT besides fare payment methods such as station placement, design, and the built environment. The research methodology was designed to be transferable to any transit route with APC-AFC datasets' availability to identify factors contributing to DT and guide future effective policy making.

1.2.2 Public transit accessibility and transit gap causality analysis. The PTA and transit gap causality analysis research objectives were defined as the following:

1) Devise an innovative algorithm for calculating dynamic PTA, while significantly reducing the computational time that makes it feasible to perform on a normal desktop computer;
2) Implement the dynamic PTA algorithm in a low-level programming language (e.g., C++) to develop an open-source toolbox that will take advantage of publicly available data (i.e., GTFS and census data);
3) Use the toolbox to measure high-resolution dynamic PTA for a relatively large transit network, and define an unified unit-less range-free index that is able to capture the temporal fluctuation of dynamic PTA;
4) Define and measure the public transit service gap to identify regions with transit mismatches by comparing dynamic PTA (as supply) and the public transit needs (as demand), and identify the causation of mismatch by jointly using public transit accessibility gap and the unified ratio.

To achieve the first two objectives, a relatively small transit network was used as the testbed for algorithm and toolbox testing. The computational time of the algorithm on a small transit network is relatively short, thus enabling multiple run time comparisons with other available software. For this purpose, the transit network (operated by SUNTRAN) in the City of St. George, Utah is selected. GTFS data consisting of six bus routes' schedules of SUNTRAN's network were collected. The population density of geographic locations reachable by transit network were calculated from census block data. Both GTFS and census data are open-source and available for public.

An innovative dynamic (time-dependent) all-pair shortest path algorithm based on transit network characteristics was designed to measure travel times from each transit stop to all other transit stops for varying departure times throughout the day. The proposed algorithm starts from each transit stop as origin, follows the next available trip (or trips) passing through this stop, and traces this trip (or trips) to meet new stops. The travel times from origin to these stops are then updated. If the met stops are connected to new routes, then the next available trips on the new routes are traced as well. This process continues until either all the stops in the network are met or the trips appear impractical from users' perspective (e.g., nonviable number of transfers or walking distance required).

The superiority of the proposed algorithm in contrast to the fastest all-pair shortest path algorithm (to date) was mathematically proven by comparing their associated time complexity. It has been shown that as the network size increases, the time complexity of the proposed algorithm increases at a slower rate than its peers. The algorithm was coded in C++ and a toolbox was developed for calculating dynamic PTA. The computational time for calculating time-dependent all-pair shortest path and dynamic PTA for the SUNTRAN's transit network was measured using the proposed algorithm, fastest algorithm (Pettie's algorithm (*44*)), and Esri's ArcMap Network Analyst. The results show that the proposed algorithm outperforms others, and above all allows such computation on a normal desktop computer. Analysis shows that headway, operating speed, stop positioning, and schedule coordination might all influence the temporal fluctuation of travel time and PTA. It thus motivates further exploration of unified ratio to capture such temporal fluctuation of PTA.

Following Objectives 3 and 4, the UTA's transit network was selected as the analysis location due to its relatively large transit network covering six counties with 125 transit routes encompassing bus, light rail, and commuter rail. The GTFS data for UTA's network, which is publicly accessible, were collected from the GTFS-data-exchange website (*45*) to be used for measuring travel times between transit stops. The socioeconomic data regarding job density, worker density, and salary/income was obtained from the Census Transportation Planning Product (CTPP) website (*46*). The collected data were used to measure the available opportunities and the need for public transit services at each transit stop and TAZ. The Weighted Average Travel Time (WATT), which weighs travel time based on potential opportunities available, was selected as the PTA measure due to its independency of super-linearity of distance-decay function.

The developed toolbox was used to measure the WATT for each transit stop at 10-minute intervals from 4 AM to 10 PM. The potential opportunities available at each TAZ were measured as the adjusted number of jobs available based on their average salary. Potential opportunities available at each transit stop were then computed based on the potential opportunities of the TAZs intersecting within a 400-m buffer (i.e., stop catchment area) around the transit stop. The dynamic PTA computation (that required shortest path finding between about 40 million Origin-Destination (O-D) pairs) took about 6 days on a normal desktop computer. To develop an index that can capture the temporal fluctuation of PTA, several options were considered and compared. It has been shown that Average to Median WATT Ratio (AMWR), as a unified unit-less range-free index, outperforms other options in quantifying the temporal variation of WATT. The large value of AMWR indicates negligible fluctuation in PTA throughout the day and good transit service.

The Need for Public Transit Services (NPTS) of each TAZ was defined and measured as the adjusted number of workers based on their average income. The NPTS and average WATT of each TAZ were compared to measure the public transit service gap.

For this purpose, the Public Transit Accessibility Gap index (PTAG) was defined as the multiplication of WATT and normalized NPTS. The high value of PTAG indicates poor PTA (high WATT) and high NPTS. Finally, the AMWR (as a service quality indicator) was jointly used with PTAG (as a mismatch indicator) to unveil the underlying reasons of the public transit service gap – poor transit service or geographical disadvantage. The Need for Public Transit Improvement indicator (NPTI) was defined by enlarging the impact of quality of service on the public transit services gap. Such enlarging was implemented through an innovative power scaling method that normalized the NPTI values regarding the geography of study area. High value of NPTI is associated with poor PTA, high NPTS, and caused by poor transit service in the region.

This approach resulted in the ability to measure temporal fluctuation of PTA by a single index, calculate transit mismatches, and prioritize TAZs based on their need for transit improvements regardless of their geographic location. In addition, the proposed analysis provide insights about the impact of fast transit services, spatial inconvenience, and level of coordination between the feeder route and the fast route on PTA, PTAG, and NPTI. The proposed method was designed to be reproducible for any public transit network and easily modifiable for any measure of PTA (e.g., PTA to jobs, supermarkets, and gym).

1.3 Dissertation Outline

This dissertation consists of five chapters. The first chapter introduces the research problem and defines the research objectives both in general and for each specific application. The chapter ends by outlining the proposed dissertation chapters. Chapters 2, 3, and 4 demonstrate the journal publication studies conducted for each application.

Chapter 2 presents the fare payment structure and DT modeling study explaining the gaps in existing literature on the use of APC and AFC datasets for DT modeling, introducing the methodology that fills in those gaps by estimating missing variables, describing the collected data, and discussing results and implications. The third chapter presents the research on the dynamic all-pairs shortest path algorithm and toolbox that enables the high-resolution dynamic PTA calculation on a normal desktop computer. Chapter 3 reviews past studies, explains the importance of measuring the temporal fluctuation of PTA and the existing computational issues in such calculations, provides a brief description of GTFS data, describes the algorithm design, evaluates algorithm and PTA results through an application demo using St. George's transit network, and ends with a discussion on the implications and conclusions. Chapter 4 introduces the research on dynamic PTA interpretation and transit gap causality analysis, by providing a background on the current limitations, and continues with description of datasets, methods used to measure dynamic PTA, developed indexes to measure PTAG and NPTI, results of implementing the method to UTA's network, and concludes with findings of the study. Major contributions of this research, recommendations for future research efforts, and research limitations are provided in the final chapter.

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CHAPTER 2

GENETIC ALGORITHM AND REGRESSION-BASED MODEL FOR ANALYZING FARE PAYMENT STRUCTURE AND TRANSIT DWELL TIME

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Genetic Algorithm and Regression-Based Model for Analyzing Fare Payment Structure and Transit Dwell Time

S. Kiavash Fayyaz, Xiaoyue (Cathy) Liu, and Richard J. Porter

The time that buses spend at stops, also called dwell time (DT), has a direct effect on transit service reliability and operational efficiency. A practical, coherent, and quantitative DT modeling approach is needed to identify the factors that contribute most to DT. Commonly used methods for studying DT to date involve manually collected field data or the use of automatic sensors to gather information on factors influencing DT. These approaches have often suffered from limited sample sizes or the inability to provide information on nonelectronic fare payment methods (e.g., cash payment and prepaid passes), which can contribute significantly to DT. To address these gaps, this study developed a genetic algorithm and regression-based modeling approach first to estimate transit fare transactions that do not have electronic records and then to quantify the effect of a number of factors on DT. Integrating information from multiple data sources, the combined approach of optimization and regression analysis offers a data-driven evaluation of existing fare payment structures and their individual effects on DT. With the 35M bus rapid transit line operated by the Utah Transit Authority as a case study, the method demonstrates the robustness and strong prediction power in DT modeling. Results quantify the magnitude of advantages of offboard over onboard fare collections and offer some insights into the operational effects of station placement, design, and the built environment. The modeling approach is transferable to any transit route or system that is equipped with automatic passenger counters. The fare payment analysis can assist transit agencies with service optimization and performance assessments.

Transit service reliability and efficiency are influenced by the variability in bus operating times. Bus operating time consists of two main components: (*a*) time spent between stops (running time) and (*b*) time spent at stops [dwell time (DT)]. Variability in these components can result in an increase in transit headway variation and, consequently, a worsening experience for transit users because of inconsistent wait times. The DT can account for a significant portion of the bus operating time (*1*). Therefore, understanding the nature of factors influencing DT will assist transit authorities with planning and operating their bus systems more effectively.

The *Transit Capacity and Quality of Service Manual* (TCQSM) defines DT as the sum of passenger service time, boarding lost time, and door opening and closing time (*2,* p. 11-48). Passenger service time is understood to be the biggest contributor to DT, which is influenced by passenger demand, fare payments, vehicle configuration, passenger load, door usage, and platform configuration (*2*). There are also secondary factors influencing DT to various extents, such as atypical passenger boarding numbers, passenger age, time of the day, and fare payment issues (*3*). The effort to identify factors affecting transit DT has led to a wide-scale use of linear regression analysis since the 1970s (*4–13*). Similar to any statistical or econometric model, DT modeling in this way relies on a sample of data gathered via different sources to estimate model parameters. Manual data collection provides detailed and accurate data, yet typically involves labor-intensive ride checks. As a result, project budgets and time constraints usually limit the sample sizes. Recent years have seen the growing adoption by transit agencies of technologies such as systems for automatic passenger counter (APC), automatic vehicle location (AVL), and automatic fare counting (AFC), and researchers have started to use those data sources for DT modeling. Automatic data collection overcomes the main challenges presented by manually collected data, such as limited sample sizes because of time-intensive data collection, yet it also comes with downsides of its own related to resolution, accuracy, and fragmented data. For example, the effects on DT of fare transactions that do not have electronic footage have not been studied in previous work that used automatically collected data because of the absence of such information.

As one of the major factors influencing passenger service time, the fare payment structure has a direct effect on DT. Previous studies have shown that passenger boarding and alighting times depend on their fare payment method, and these findings are captured in the TCQSM methods, which include individual passenger service times by fare payment method (*2*). APC data provide the total number of passengers boarding and alighting at each station, while AFC data provide separate counts of smart card users. However, other payment options, including prepaid passes or cash transactions, cannot be traced from the APC-AFC data set, which results in the need for new analysis methods that can quantitatively identify the effect of each separately. To fill this gap, this paper introduces an effective and innovative method for estimating the fare payment structure on the basis of APC-AFC data and accurately quantifying their effects on DT. The method uses a heuristic search algorithm, specifically a genetic algorithm (GA), to compensate for missing data (e.g., cash transactions) and incorporates these results into a DT regression model. The contributions of this paper are twofold. First, a new method is introduced to categorize behavior-controlled DT observations, according to whether DT is controlled by boarding, alighting, or unique or atypical situations, which allows for the use of a simultaneous DT model on APC and

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AFC data. Second, an optimization method and regression model are combined to disaggregate the individual contributions to DT of fare payment options, station placement, design, and the built environment, a combination which constitutes a useful contribution to the literature.

Next, existing studies on DT modeling are reviewed. This review is followed by a summary of the data collection effort for this study. The modeling approach for determining fare payment structure and the effects on DT is then described, followed by an analysis of data from the Utah Transit Authority (UTA) 35M bus rapid transit (BRT). Finally, the implications are discussed.

LITERATURE REVIEW

The classic linear regression model with ordinary least squares (OLS) estimation has been widely used as the means for modeling bus DT. Previous studies have investigated a broad range of DT model specifications, from simple to multivariate regression analysis. In the simple DT models, DT is considered solely a function of the numbers of boarding and alighting passengers (*14*). In multivariate DT models, a number of different factors are considered, such as fare payment methods, crowding effect, and passenger population. The multivariate DT model is usually expressed in a format similar to that of Tirachini (*3*):

$$\mathrm{DT} = \sum_{i=0}^{N} \alpha_i * B_i + \sum_{j=1}^{2} \beta_j * A_j + C \qquad (1)$$

where

α_i = average boarding time per passenger using ith fare payment method,
B_i = corresponding number of boarding passengers,
N = number of available fare payment methods,
β_j = average alighting time per passenger using jth door,
A_j = number of alighting passengers through jth door, and
C = time spent for door opening and closing (dead time).

The multivariate models are likely a more realistic representation of a DT model, especially given the dynamics of passenger boarding and alighting.

A summary of a selected number of studies (*3, 4, 8, 14–22*) on DT modeling is shown in Table 1. The fare payment method was repeatedly shown in the literature to be a major influence on DT. Kraft and Bergen were probably among the first to have studied such effects (*15*). They found that onboard exact-change fare payment was 3 s faster than onboard change-given fare payment. Guenthner and Hamat reported marginal variation of the effect on DT from different fare payment methods (*16*). Fletcher and El-Geneidy determined that onboard cash fare payers had boarding times 2 s slower than those of prepaid pass holders (*17*). Tirachini reported that DT per passenger boarding and paying with cash exact fare was 7 s less than a passenger paying with cash change given (*3*). Milkovits analyzed the effect of fare payment methods and found that smart media cards were roughly 1.5 s faster to process than were magnetic stripe tickets (*18*). Sun et al. used data of 3.3 million smart card transactions in Singapore and found that the boarding (alighting) interval per passenger using a smart card was about 1.9 s (1.5 s) (*19*). A closer review of these studies showed that the estimated effect of individual fare payment methods varied across routes and transit systems. For example, boarding time for the magnetic strip fare payment method was estimated to be 4.8 s in the Milkovits study (*18*) but 5.5 s in Tirachini (*3*). While these different estimates reveal possible variations in the effect of fare payment structure resulting from interactions with other key variables or indicate potential omitted (confounding) variable issues, the data are conclusive in one important aspect: they reveal that different payment structures triggered changes in DT and that the effect of different payment methods was uncovered in study after study. In other words, fare payment strategies can be implemented to improve the reliability of transit operation by reducing DT magnitudes and variation.

TABLE 1 Selection of Previous Studies on DT Modeling

Study	Data Collection Method	Sample Size	Factors Studied
Feder (*4*)	Manual	NA	Boarding and alighting
Kraft and Bergen (*15*)	Manual	NA	Time of day, fare payment method
Levinson (*14*)	Manual	NA	Boarding and alighting
Guenthner and Hamat (*16*)	Manual	266 passengers observed	Boarding and alighting, fare payment method
Lin and Wilson (*20*)	Manual	NA	Dwell time per door, crowding effect
Aashtiani and Iravani (*21*)	Manual	3,454	Number of doors used, boarding and alighting, crowding effect
Rajbhandari et al. (*22*)	APC-AVL	40,594	Boarding and alighting, crowding effect, time of day
Dueker et al. (*8*)	APC-AVL	350,000	Lift operation, time of day, crowding, schedule adherence, boarding and alighting
Milkovits (*18*)	APC-AVL-AFC	173,750	Fare payment method, alighting through each door, crowding effect
Fletcher and El-Geneidy (*17*)	Manual	1,746	Crowding effect, fare payment method
Tirachini (*3*)	Manual	1,604	Crowding, passenger age, fare payment method
Stewart and El-Geneidy (*13*)	APC-AVL	1,213,691	Boarding and alighting through each door, crowding effect, presence of traffic light, stop effect
Sun et al. (*19*)	AFC-APC	3,300,000	Smart card users' time interval, crowding

NOTE: NA = not available.

The aforementioned studies on DT and the fare payment method can be categorized on the basis of data sources for model estimation purposes, usually either manual or automatic data collection. While both sources face their own challenges and limitations in the study of fare payment effects, automatic data collection has steadily become a more promising option because of the massive amount of information that can be gathered and the cost-effectiveness of doing so. Yet resorting solely to automatic data collection might, at times, downplay the significance of payment methods that do not have electronic footage, which are indeed still popular in a large number of transit systems, leaving their effect unknown or unjustified. This paper seeks to address this limitation by using optimization and regression approaches to provide a fuller analysis of fare payment structure and uncover its effect on DT.

DATA COLLECTION

UTA is the primary public transit provider in Salt Lake City, Utah, and in Davis, Weber, Box Elder, and Tooele Counties in the state of Utah. The growth of economic development and opportunities necessitated mobility enhancements in these counties, especially via public transit in recent decades. The ambitious program of transit construction, led by UTA, has simultaneously spanned across light rail (LRT-TRAX), bus rapid transit (BRT-MAX), commuter rail (Front-Runner), streetcars, and buses (local, express, and special purpose) since the 1990s. Of all the transit options available, BRT offers a unique service by combining the flexibility of buses with the efficiency of rail. The 35M MAX BRT was the first BRT line in Salt Lake City, with UTA starting its operation in 2008. The bus runs a 10.8-mi distance on the 3300 S/3500 S corridor connecting the suburban town of Magna, Utah, and the light rail station at Millcreek. Following in the footsteps of the 35M BRT pioneer project, several BRT lines are also being planned in the very near future (5600 West, Provo–Orem, Utah, 4700 South, and 3300 South). The lessons learned and data gathered from 35M MAX can thus be directly applied for informed planning, design, and ultimately enhanced performance of these future projects. The 35M BRT uses low-floor, three-door buses that are 40 ft in length. The buses have 28 seats and 32 standees, totaling a capacity of 60 passengers. The 35M BRT buses run on 15-min headways on weekdays and 30-min headways every Saturday. The buses use on average about 45% of their capacity during peak hours; thus a crowding condition rarely occurs. Several fare payment options are available, including onboard cash payments with exact change into the fare box, electronic fare payments with a smart card, prepaid tickets purchased from a ticket vending machine (TVM), and transfer tickets. The 35M BRT drivers are instructed to use all doors for boarding and alighting and no fare inspection is required; thus some fare evasion is expected. All three doors are equipped with smart card readers (tap on and off), and only passengers who wish to use onboard cash payments are required to board at the front door. A TVM is located at every BRT station, and no fare validation on boarding is necessary. The direct benefit of TVMs is the reduction in DT and operational delays associated with collecting a fare and the resulting interaction between drivers and passengers. Thus 35M BRT provided an excellent platform for DT and fare payment structure analysis, with the modeling results being potentially useful to inform the upcoming BRT project designs.

Figure 1 shows the 35M MAX BRT route layout. The BRT line starts at the Millcreek Station and ends at the 3500 South 800 West Station. The Magna loop is not part of the BRT line; however, the same fleet is used to operate that segment. The 35M BRT line uses center-running dedicated lanes along 3500 South between 2810 West and 3600 West and runs in mixed traffic for the rest of the route (right-of-way C). There are 14 stations in each direction (totaling 28 stations).

To model DT and the fare payment structure quantitatively, stop-level data were needed. Data used in this study were collected through APC-AFC systems, with the use of sample manual checks for validation purposes. APC-AFC records were obtained for May 2014. The APC records included a total of 34,937 observations for 28 stops and provided information on travel direction, station ID and location, bus departure and arrival time, DT, number of boarding and alighting passengers, and station spacing at every station. AFC records included a total of 24,121 observations, with each entry representing individual passenger tap-on (boarding) or tap-off (alighting) at a specific date, time, and station. AFC and APC data were postprocessed for matching on the basis of the following criteria: (*a*) AFC and APC records should have the same date and (*b*) the same station ID and (*c*) the time stamp difference between the matching records is less than 2 min (to accommodate any measurement error). If AFC and APC data entries matched each other, then the AFC record was added to the corresponding APC observation. When an abnormal match appeared (e.g., AFC boarding greater than the total boarding), the record was removed from the data set. This process was completed with C++. Quality checks were also applied to the APC data set for sensor detection malfunction. A DT that was longer than 3 min or an average DT per passenger that was less than 1 s was considered an erroneous data record.

To validate further the automatic data collection and modeling results, a testing data set was collected to compare against the electronic data. Manual data collection was conducted on February 10, 2015, along 35M BRT during three peak periods (7 to 9 a.m., 11 a.m. to 1 p.m., and 4 to 6 p.m.). The data recorded consisted of 120 observations of the number of onboard cash payers and prepaid pass holders. In addition, 3,340 APC and 975 AFC records were gathered for that day, and the same matching process was conducted. The 120 manually collected observations were integrated into the APC-AFC database for model validation.

METHOD

GA for Determining Behavior-Controlled DT

Bus DT generally is influenced by the number of passengers boarding or alighting or by atypical passenger activities (e.g., bike or disabled passenger boarding and alighting). The consensus of DT modeling distinguishes between sequential and simultaneous boarding and alighting. The sequential model assumes that passenger activities (boarding and alighting) occur subsequently, and the DT is modeled as follows:

$$\text{DT} = \sum_{j=1}^{A} t_j^a + \sum_{j=1}^{B} t_j^b + \text{dead time} \tag{2}$$

where

A and B = numbers of alighting and boarding passengers, respectively;
t_j^a and t_j^b = times that passenger j takes to alight or board, respectively; and
dead time = time needed to open and close bus doors.

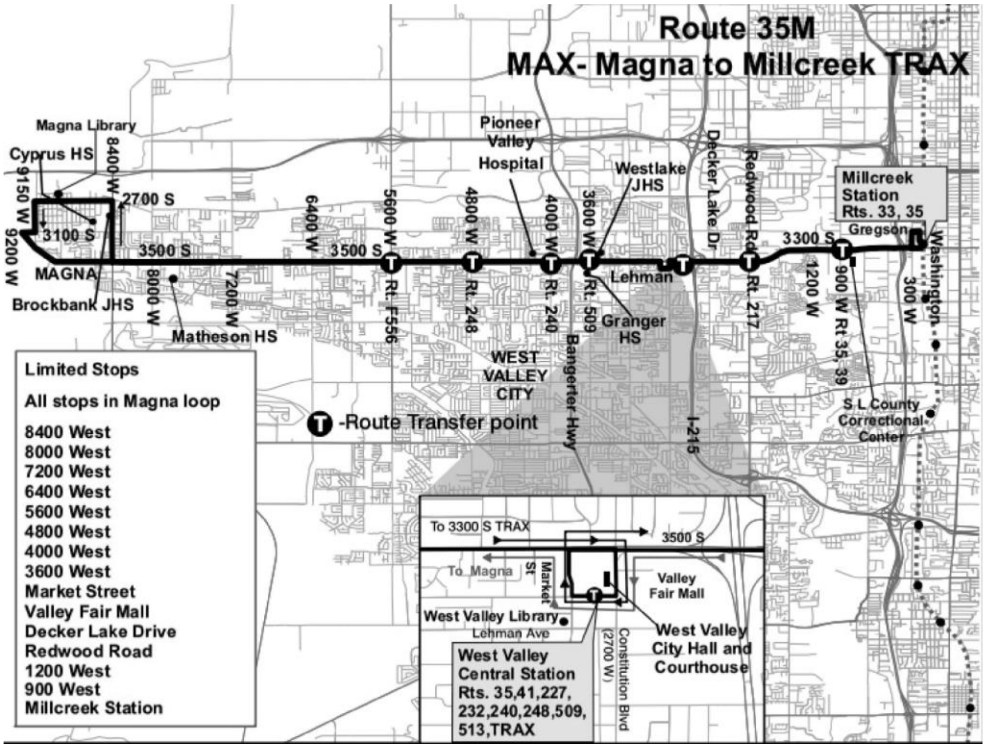

FIGURE 1 BRT 35M route layout (rts. = routes; HS = high school; JHS = junior high school; SL County = Salt Lake County). (Source: www.rideuta.com.)

In the case of simultaneous boarding and alighting, in which boarding and alighting occur at the same time, DT is modeled as follows:

$$\text{DT} = \max\left\{\sum_{j=1}^{A} t_j^a, \sum_{j=1}^{B} t_j^b, \text{atypical}\right\} + \text{dead time} \qquad (3)$$

On the basis of field observation, the simultaneous model is applicable to 35M BRT. The simultaneous model formulation indicates that the APC-AFC data set for modeling DT needs to be divided into three separate classes: boarding controlled (BC), alighting controlled (AC), and atypical situations.

BC refers to observations in which

$$\max\left\{\sum_{j=1}^{A} t_j^a, \sum_{j=1}^{B} t_j^b, \text{atypical}\right\} = \sum_{j=1}^{B} t_j^b$$

AC refers to observations in which

$$\max\left\{\sum_{j=1}^{A} t_j^a, \sum_{j=1}^{B} t_j^b, \text{atypical}\right\} = \sum_{j=1}^{A} t_j^a$$

Atypical scenarios refer to observations in which

$$\max\left\{\sum_{j=1}^{A} t_j^a, \sum_{j=1}^{B} t_j^b, \text{atypical}\right\} = \text{atypical}$$

Separate DT models are needed for each class, and for this paper, focused on fare payment effects, it is the BC observations that are of primary interest. Atypical scenarios are defined as scenarios with DT per boarding passenger of longer than 10 s and DT per alighting passenger of longer than 5 s. These values were chosen because they are about twice the estimated time of average passenger activities (see Table 2) (*18*). In addition, the field observation attested that the fastest biker boarding time was approximately 10 s. To separate BC and AC data sets, the GA was applied to the APC-AFC records in MATLAB. The GA is a heuristic search process that is commonly used to generate solutions for optimization problems. Given an objective function, the GA uses a random number generator to populate alternatives at each iteration. The process continues until an optimal solution is reached. The objective function for distinguishing BC and AC data sets was expressed as

GA:

$$\text{minimize}\left(\text{abs}\left(\text{DT}_{\text{estimated}_i} - \text{DT}_{\text{actual}_i}\right)\right) \qquad (4)$$

TABLE 2 Optimal Model Specification with B-CTVM

DT Scenario[a]	Coefficient	SE	t	$P > \|t\|$
Weekend	1.411	0.349	4.04	.000
B-EFC	4.992	0.163	30.64	.000
B-CTVM	3.329	0.047	71.46	.000
A-EFC	2.623	0.418	6.28	.000
A-CTVM	1.741	0.075	23.14	.000
DoorCycle	1.580	0.196	8.06	.000
Fair Mall stop indicator (Magna direction)	2.478	0.390	6.36	.000
3575 West stop indicator	−2.598	0.525	−4.95	.000
3955 West stop indicator	2.222	0.413	5.38	.000
Fair Mall stop indicator (TRAX direction)	3.766	0.560	6.72	.000
1685 West stop indicator	2.479	0.456	5.44	.000
Constant	2.411	0.290	8.32	.000

NOTE: SE = standard error. R^2 = .5943; adjusted R^2 = .5937; $F(11, 7{,}713)$ = 1,027.05; Prob > F = .00.
[a]Variables are significant at the 99% confidence level.

where

$$\text{DT}_{\text{estimated}_i} = \max\left\{\sum_{j=1}^{A} t_j^a, \sum_{j=1}^{B} t_j^b\right\} + \text{dead time} \quad (5)$$

$$\sum_{j=1}^{A} t_j^a = B_{\text{EFC}_i} * T_{\text{EFC}_i} + B_{\text{non-EFC}_i} * T_{\text{non-EFC}_i} \quad (6)$$

$$\sum_{j=1}^{B} t_j^b = A_i * T_{\text{alighting}_i} \quad (7)$$

with the following constraints based on previous studies and field observations:

$2 \text{ s} \le T_{\text{EFC}_i} \le 8 \text{ s}$

$2 \text{ s} \le T_{\text{non-EFC}_i} \le 10 \text{ s}$

$1 \text{ s} \le T_{\text{alighting}_i} \le 5 \text{ s}$

$1 \text{ s} \le \text{dead time} \le 6 \text{ s}$

where

B_{EFC_i} and $B_{\text{non-EFC}_i}$ = numbers of boarding passengers with and without smart card electronic fare collection (EFC) payment, respectively, for ith observation (where one observation is stop of bus for boarding and alighting);
A_i = number of alighting passengers for ith observation;
T_{EFC_i} and $T_{\text{non-EFC}_i}$ = average boarding times for smart card users and nonusers, respectively, for ith observation; and
$T_{\text{alighting}_i}$ = average alighting time for ith observation.

Heuristic searches that are part of a GA were used to determine optimal estimates of T_{EFC_i}, $T_{\text{non-EFC}_i}$, and $T_{\text{alighting}_i}$, given the defined constraints, and consequently whether the ith observed DT was boarding- or alighting-controlled. Following this process, 7,725 APC observations were identified as BC, and 3,279 were identified as AC. The summary statistics of BC observations are shown in Table 3. Given the objectives of this paper, these BC observations became the focus of the rest of the analysis.

DT Modeling and Fare Payment Structure Analysis

After all APC observations were categorized, atypical scenarios were excluded from the modeling effort as they might contain irreproducible features or belong to rare situations. To estimate the fare payment structure and its effect on DT, especially those methods that do not have an electronic footprint, BC-related APC observations are used in the analysis from this point forward. AC-related data were excluded because onboard cash payers and prepaid pass holders share the same alighting behavior (no tap-off or transaction-related activity required) whereby additional information for separating these two fare payment methods can be obtained from BC-related APC records (e.g., different boarding or transaction time).

Multivariate regression was adopted for DT modeling in this study. The DT was represented as a linear collective function of independent variables, expressed as

$$\text{DT}_i = \boldsymbol{\beta} * \boldsymbol{X}_i + \varepsilon_i \quad (8)$$

TABLE 3 Summary Statistics of BC Observations

Variable	Mean	SD	Min.	Max.	Sum
DT	17.055	13.270	4.8	169.8	na
Weekend	0.084	0.277	0	1	na
B-EFC	0.263	0.610	0	8	2,033
B-CTVM	2.689	2.282	0	18	20,692
A-EFC	0.051	0.235	0	3	396
A-CTVM	0.917	1.443	0	16	7,087
DoorCycle	1.288	0.496	0	5	na
Fair Mall stop (Magna direction)[a]	0.083	0.276	0	1	na
3575 West stop[a]	0.035	0.185	0	1	na
3955 West stop[a]	0.059	0.235	0	1	na
Fair Mall stop (TRAX direction)[a]	0.035	0.183	0	1	na
1685 West stop[a]	0.049	0.215	0	1	na

NOTE: DT = measures the time (s) between when first doors open to last doors close; na = not applicable; B-EFC = number of passengers boarding using electronic fare payment, or number of passengers who use Electronic Fare Collection (EFC) method, recorded by AFC; A-EFC = number of passengers alighting using EFC, recorded by AFC; B-CTVM = number of boarding passengers using nonelectronic fare payment; A-CTVM = number of alighting passengers using nonelectronic fare payment; Weekend = indicator that shows whether the observation is on weekend (1) or on weekday (0); Door-Cycle = shows how many time bus doors were opened and closed during the observation, recorded by APC. Number of observations for all variables = 7,725.
[a]Indicator shows the station at which the observation was collected. These specific stations are presented in the table because of their ultimate significant impact on DT (see Tables 3 and 5), with other stations showing no unique effects.

where

DT_i = DT for ith observation,
$\boldsymbol{\beta}$ = vector of estimable coefficients associated with each right-hand-side variable,
$\boldsymbol{X_i}$ = vector of measurable characteristics that determine DT for ith observation, and
ε_i = disturbance term.

The vector $\boldsymbol{X_i}$ in Equation 8 includes all variables in Table 1 plus a constant term (dead time). Therefore the model can be rewritten as

$$\begin{aligned}\mathrm{DT}_i = {} & \boldsymbol{\beta}_{\text{weekend}} * \text{weekend}_i + \boldsymbol{\beta}_{B_{\text{EFC}}} * B_{\text{EFC}_i} + \boldsymbol{\beta}_{B_{\text{CTVM}}} * B_{\text{CTVM}_i} \\ & + \boldsymbol{\beta}_{A_{\text{EFC}}} * A_{\text{EFC}_i} + \boldsymbol{\beta}_{A_{\text{CTVM}}} * A_{\text{CTVM}_i} + \boldsymbol{\beta}_{\text{DoorCycle}} * \text{DoorCycle}_i \\ & + \boldsymbol{\beta}_{\text{FairMall stop(Magna direction)}} * \text{Fair Mall stop}(\text{Magna direction})_i \\ & + \boldsymbol{\beta}_{3575\text{ W stop}} * 3575\text{ W stop}_i + \boldsymbol{\beta}_{3955\text{ W stop}} * 3955\text{ W stop}_i \\ & + \boldsymbol{\beta}_{\text{FairMall stop(TRAX direction)}} * \text{Fair Mall stop}(\text{TRAX direction})_i \\ & + \boldsymbol{\beta}_{1685\text{ W stop}} * 1685\text{ W stop}_i + C + \varepsilon_i \end{aligned} \tag{9}$$

where

$\boldsymbol{\beta}_{\text{variable name}}$ = parameter estimates associated with that particular right-hand-side variable,
$B_{\text{CTVM}i}$ = total number of prepaid pass holders (B-TVM) and onboard cash payers (B-cash) in ith observation,
$A_{\text{EFC}i}$ = number of passengers alighting and using EFC in ith observation,
station name_i = station dummy variable indicating station of ith observation, and
C = constant term representing portion of dead time that driver spent to ensure that door area was cleared.

In Equation 9, B-CTVM accounts for the total number of prepaid pass holders (B-TVM) and onboard cash payers (B-cash). To distinguish the two sets of the passenger population on the basis of fragmented APC data, a search algorithm was applied. Assume that all independent variables in the model are fixed in repeated samples and therefore independent of the error term; their parameter estimates should remain the same when B-CTVM is replaced with B-TVM and B-cash. As a result, Equation 9 can be further rewritten as

$$\begin{aligned}\mathrm{DT}_i = {} & \boldsymbol{\beta}_{\text{weekend}} * \text{weekend}_i + \boldsymbol{\beta}_{B_{\text{EFC}}} * B_{\text{EFC}_i} + \boldsymbol{\beta}_{B_{\text{TVM}}} * B_{\text{TVM}_i} \\ & + \boldsymbol{\beta}_{B_{\text{cash}}} * B_{\text{cash}_i} + \boldsymbol{\beta}_{A_{\text{EFC}}} * A_{\text{EFC}_i} + \boldsymbol{\beta}_{A_{\text{CTVM}}} * A_{\text{CTVM}_i} \\ & + \boldsymbol{\beta}_{\text{DoorCycle}} * \text{DoorCycle}_i + \boldsymbol{\beta}_{\text{FairMall stop(Magna direction)}} \\ & * \text{Fair Mall stop}(\text{Magna direction})_i + \boldsymbol{\beta}_{3575\text{ W stop}} \\ & * 3575\text{ W stop}_i + \boldsymbol{\beta}_{3955\text{ W stop}} * 3955\text{ W stop}_i \\ & + \boldsymbol{\beta}_{\text{FairMall stop(TRAX direction)}} * \text{Fair Mall stop}(\text{TRAX direction})_i \\ & + \boldsymbol{\beta}_{1685\text{ W stop}} * 1685\text{ W stop}_i + C + u_i \end{aligned} \tag{10}$$

From Equations 9 and 10, the following can be concluded:

$$\boldsymbol{\beta}_{B_{\text{CTVM}}} * B_{\text{CTVM}_i} + \varepsilon_i = \boldsymbol{\beta}_{B_{\text{cash}}} * B_{\text{cash}_i} + \boldsymbol{\beta}_{B_{\text{TVM}}} * B_{\text{TVM}_i} + u_i \tag{11}$$

where $\boldsymbol{\beta}_{B_{\text{cash}}}$ and $\boldsymbol{\beta}_{B_{\text{TVM}}}$ are the parameter estimates associated with B-cash and B-TVM variables, respectively, and u_i is the error term of the ith observation in the updated model.

The optimal OLS model will yield an estimate for $\boldsymbol{\beta}_{B_{\text{CTVM}}}$. Yet given the unavailability of data, $\boldsymbol{\beta}_{B_{\text{cash}}}$, B_{cash_i}, $\boldsymbol{\beta}_{B_{\text{TVM}}}$, B_{TVM_i}, and B_{cash_i} are unknown in Equation 11. Thus, the GA was used again to estimate the fare payment structure and the individual effects on DT.

The optimization problem for determining the fare payment structure can be expressed as

$$\text{GA: } \min\left[\text{abs}\left\{\begin{matrix}\left(\boldsymbol{\beta}_{B_{\text{CTVM}}} * B_{\text{CTVM}_i} + \varepsilon_i\right) \\ -\left(\alpha_{B_{\text{cash}_i}} * B_{\text{cash}_i} + \alpha_{B_{\text{TVM}_i}} * B_{\text{TVM}_i}\right)\end{matrix}\right\}\right] \tag{12a}$$

subject to

$$B_{\text{cash}_i}, B_{\text{TVM}_i} \in \mathbb{Z} \tag{12b}$$

$$B_{\text{CTVM}_i} = B_{\text{cash}_i} + B_{\text{TVM}_i} \tag{12c}$$

$$\boldsymbol{\beta}_{B_{\text{cash}}} > \boldsymbol{\beta}_{B_{\text{CTVM}}} > \boldsymbol{\beta}_{B_{\text{TVM}}} \tag{12d}$$

$$\text{slowest } B_{\text{TVM}} > \alpha_{B_{\text{TVM}_i}} > \text{fastest } B_{\text{TVM}} \tag{12e}$$

$$\text{slowest } B_{\text{cash}} > \alpha_{B_{\text{cash}_i}} > \text{fastest } B_{\text{cash}} \tag{12f}$$

$$\text{average } \alpha_{B_{\text{TVM}_i}} \cong \boldsymbol{\beta}_{B_{\text{TVM}}} \tag{12g}$$

$$\text{average } \alpha_{B_{\text{cash}_i}} \cong \boldsymbol{\beta}_{B_{\text{cash}}} \tag{12h}$$

$$u_i = 0 \tag{12i}$$

where $\alpha_{B_{\text{TVM}_i}}$ and $\alpha_{B_{\text{cash}_i}}$ are the average boarding times for B-TVM and B-cash, respectively, and slowest $B_{\text{TVM}}/B_{\text{cash}}$ (fastest $B_{\text{TVM}}/B_{\text{cash}}$) refers to the maximum (minimum) average boarding time for prepaid pass holders and onboard cash payers, separately.

Constraints 12*b* and 12*c* are integrality constraints and ensure that the number of onboard cash payers and prepaid pass holders total to B-CTVM. Constraints 12*d* through 12*f* are set on the basis of previous studies and the authors' field observations. Those constraints ensure that the average boarding time for prepaid pass holders is shorter than for onboard cash payers given the assumption that no additional interaction exists with their boarding. The approximate equivalence between $\boldsymbol{\beta}_{B_{\text{TVM}}}/\boldsymbol{\beta}_{B_{\text{cash}}}$ and $\alpha_{B_{\text{TVM}}}\text{i}/\alpha_{B_{\text{cash}_i}}$ given by Constraints 12*g* and 12*h* ensures that the variability of the boarding time for each observation is fully captured. Constraint 12*i* is proved in the following proposition: if the optimal OLS model includes all independent variables that affect DT, except for B-cash and B-TVM, then ε_i in Equation 11 captures solely the variability introduced by B-cash and B-TVM. Thus, by including these two variables in the updated model (Equation 11), the new error term $u_i \sim 0$, as there exists no other unexplained variation for DT.

The result of applying a GA to solve Equation 12*a* provides estimates for B-cash and B-TVM for each individual observation. Thus, the parameters in Equation 10 can be estimated with OLS to identify quantitatively the effects of all variables on DT.

MODELING RESULTS, RESULTS INTERPRETATION, AND VALIDITY TESTING

Fare Payment Structure Analysis and DT Modeling

Following the modeling process presented above, the result of the optimal OLS model with B-CTVM is presented in Table 2. The parameters associated with all of the independent variables are statistically significant, and the model shows acceptable goodness of fit with an adjusted R^2-value of .59. As shown in Table 2, DT is a function of weekend, B-EFC, B-CTVM, A-EFC, A-CTVM, door-cycle, five different individual stop indicators, and an intercept. Even though the model used only BC-related APC observations, the effect of alighting passengers was statistically significant. This finding is largely a result of the fact that, in reality, there rarely exist perfect simultaneous or sequential boarding and alighting. The optimal model was selected through extensive specification testing to find the most logical and informative model.

To replace B-CTVM further with the estimated number of prepaid pass holders and onboard cash payers, Equation 12*a* was solved with the GA. Constraints 12*e* and 12*f* needed to be further defined on the basis of field observation and the literature. The TCQSM provides an estimated boarding time range of 1.75 to 2.5 s/passenger with no fare payment (which is similar to times for prepaid pass holders, transfer ticket holders, or fare evaders), and 3.1 to 8.4 s/passenger with onboard cash payment [Exhibit 6-4, TCQSM (*2*)]. In addition, the field observations indicated that boarding time for prepaid pass holders took up to 4.5 s/passenger. The optimal model result presented in Table 2 for B-CTVM (3.3 s/passenger) was used to define further the lower boundary for onboard cash payers. Thus Constraints 12*e* and 12*f* were updated as

$$4.3 \text{ s} > \alpha_{B_{\text{TVM}_i}} > 1.3 \text{ s} \quad (13)$$

$$7.3 \text{ s} > \alpha_{B_{\text{cash}_i}} > 3.3 \text{ s} \quad (14)$$

The GA thereby yielded the estimated number of cash payers and prepaid pass holders for each APC observation (B-cash and B-TVM). Summary statistics of the results are shown in Table 4.

The outcome presented in Table 4 was integrated in the OLS model for new coefficients estimation of DT, where B-CTVM was replaced with B-cash and B-TVM as explained in Equation 9. The final model specification is shown in Table 5.

The final model demonstrates excellent goodness of fit with an adjusted R^2-value of .90. Parameters associated with all variables in the specification are statistically significant. In the sections to follow, results interpretation is discussed at length and potential estimation concerns arising from the GA assumptions presented are addressed by conducting validity testing.

TABLE 4 Summary Statistics of B-Cash and B-TVM

Variable	Mean	SD	Min.	Max.	Sum
B-TVM	1.743	2.163	0	18	13,467
B-Cash	0.935	1.605	0	12	7,225

NOTE: Number of observations = 7,725.

TABLE 5 Final Optimal Model Specifications with B-TVM and B-Cash

DT Model Specification[a]	Coefficient	SE	t	$P > \lvert t \rvert$
Weekend	1.087	0.173	6.30	.000
B-EFC	5.279	0.081	65.57	.000
B-TVM	1.803	0.025	73.03	.000
B-Cash	6.917	0.033	211.68	.000
A-EFC	2.020	0.206	9.79	.000
A-CTVM	1.611	0.037	43.40	.000
Door-Cycle	1.509	0.097	15.60	.000
Fair Mall stop indicator (Magna direction)	2.116	0.192	11.00	.000
3575 West stop indicator	−2.588	0.259	−9.98	.000
3955 West stop indicator	1.617	0.204	7.92	.000
Fair Mall stop indicator (TRAX direction)	3.432	0.277	12.40	.000
1685 West stop indicator	2.287	0.225	10.15	.000
Constant	2.026	0.143	14.15	.000

NOTE: R^2 = .9011; adjusted R^2 = .9009; $F(12, 7{,}712)$ = 5,852.99; Prob > F = .00.
[a]Variables are significant at the 99% confidence level.

Results Interpretation

The final DT model showed a good statistical fit with an adjusted R^2-value of .90. All estimated variable coefficients were statistically significant and had plausible signs. The model interpretation and implications are discussed below.

Boarding

The average estimated boarding time for EFC users was about 5.2 s/passenger, which was much longer than the time (2.75 s) suggested by the TCQSM (*2*). Two possible reasons may contribute to the difference: the tap-on–tap-off EFC reader on the UTA fleet has slower refresh rates compared with the common smart card reader systems used in the United States, and a significant portion of EFC users delayed their boarding process by searching for the card (according to field observations).

The average boarding time for passengers who used prepaid passes, transfer tickets, or fare evasion was about 1.8 s/passenger, which matches the TCQSM suggestion (1.75 s/passenger) (*2*). The average boarding time for passengers who paid their fare by cash was about 6.9 s/passenger, which was approximately 2.5 s/passenger longer than the time suggested by TCQSM (4.5 s/passenger) (*2*). This difference may be largely the result of the fact that a sizable portion of passengers did not have the exact cash ready before boarding. The boarding time for onboard fare payers (including cash payers and smart card users) was considerably higher than for offboard fare payers (prepaid pass holders and transfer ticket users). By eliminating the onboard cash payment on 35M BRT (assuming that all cash payers will switch to prepaid passes), DT can be reduced by at least 30 min/day just for BC-related observations.

Alighting

Because of the nature of data used for DT modeling, only BC-related APC observations were used in this study. Thus it was expected that the alighting time in the model would be lower than the TCQSM's suggestion, given the limited effect of alighting time in the data used for model estimation. The average alighting times for EFC users and non-EFC users were 2.0 s/passenger and 1.6 s/passenger, respectively, which are indeed less than the TCQSM-suggested alighting times (3.5 and 1.75 s/passenger, respectively) (*2*).

Stop Characteristics

One critical factor affecting DT that is often neglected in most of the previously published studies is stop placement, design, and built environment. The large sample of data provided by APC offered a unique opportunity to explore the effect of stop characteristics on DT to an extent allowable by the data characteristics.

The parameter estimates for the Fair Mall stop indicator showed that, on average, the DT is 2.1 s (for Magna direction) and 3.4 s (for TRAX direction) longer than other stops. This finding is highly likely to be a result of the longer service time required for passengers carrying shopping bags. A shorter expected DT (by 2.6 s) was estimated for the 3527 West stop. Being the only stop along the route that is placed on the median of the roadway, the built environment appears to better prepare passengers for an effective boarding. The 3955 West stop suffered from a longer-than-expected DT (2.2 s more), possibly because it is close to a hospital. Possibly because of its serving as a transfer stop, 1685 West had a longer-than-expected DT (2.5 s); bus drivers tend to intentionally elongate the boarding time for passengers to complete their transfer between Bus Route 217 and 35M.

Dead Time

Dead time consists of the time for door opening and closing and any additional time consumed. The DT model incorporated dead time by including the door cycle variable and the constant term (*C*). According to the model estimation results shown in Table 5, dead time can be expressed as

$$\text{dead time} = 1.5 * \text{DoorCycle} + 2 \tag{15}$$

In reality, the door is open and closed at least once at each stop (that has a DT). Thus, the minimum estimated dead time was 3.5 s.

Miscellaneous Factors

Miscellaneous variables that could affect DT, such as time of day, day of the week, and crowding effects, were also explored. The day-of-the-week variable yielded statistically insignificant effects on DT according to the model; however, it does predict that the weekend is prone to have longer expected DTs.

To capture the crowding effect, different variables—such as crowding variable = (passenger load − seating capacity)^2 * (boarding + alighting), used by Milkovits (*18*)—were tested in the model. However, the crowding variables were determined either not to be statistically significant or not to have a logically meaningful effect on DT. Data analysis showed that only 148 out of 7,725 (1.9%) BC observations experienced a load of more than 28 passengers (seating capacity). Approximately only 0.1% of BC observations experienced a load exceeding 58% of capacity (35 passengers), which was used as a threshold for identifying the crowding effect in many studies (60% of capacity). Thus, crowding rarely occurred on 35M. Analysis also showed that in the model, time of day had only a limited effect on DT, which is consistent with the findings presented in Rajbhandari et al. (*22*).

Testing Model Validity

Three posterior tests were conducted for model diagnosis and to ensure its validity.

Seemingly Unrelated Estimation Test

The seemingly unrelated estimation test was applied to both models presented in Tables 4 and 5 (*23*). The purpose of the test, similar to the Hausman specification test, was to assess the consistency of parameter estimates of the common variables (*24*). A seemingly unrelated estimation system comprises several individual relationships that are linked by the fact that their disturbances are correlated. Its typical applications are tests for intramodel and cross-model hypotheses. In the present modeling context, the null hypothesis is that all of the parameter estimates of the common variables in the two models are equal. The results ($\chi^2 = 8.09$, $\Pr > \chi^2 = .62$) indicate the consistence of the coefficients of common variables in the two models (do not reject the null hypothesis). This finding suggests that the estimated coefficients of B-cash and B-TVM do not capture additional effects on DT from other variables, and thus solely represent B-CTVM.

Model Testing and Validation

The developed DT model (shown in Table 5) was applied to the testing data set for performance assessment. With the APC-AFC data collected on February 10, 2015, the GA presented in Equation 11 was solved for the estimation of B-cash and B-TVM. The result was compared against 120 manually collected records. The GA estimation matched ground truth data in 110 observations (92%), and the rest had minimal errors (one passenger bias). The error was usually caused by the fact that not all the cash boarding followed the upper and lower boundaries set in the model. For example, sometimes the cash payment transaction for the last passenger was completed after the bus started moving, which goes beyond the assumed lower boundary for cash payers. The total number of estimated B-cash was approximately 10% higher than the ground truth data in these cases.

Testing for Possible Bias in Parameter Estimation

Coefficient estimation error introduces bias into the model and, when used for prediction, can result in imprecise forecasting. The purpose of this test was to determine the magnitude of this possible bias in the estimated parameters. The model validation process showed that error occurs when the numbers of cash payers and prepaid pass holders are estimated when compared against ground truth data (within 10% difference of the number of cash payers), and measurement error is introduced into these right-hand-side variables. Measurement error in right-hand-side variables can result in bias of the OLS estimator. To explore this further, an error range of [−15%, 15%] of total B-cash was chosen to assess the effect of measurement error in

TABLE 6 Estimation Error Impact on B-TVM and B-Cash Coefficients

Model	Number of Tests	Parameter Estimates	Lowest Value (s/passenger)	Highest Value (s/passenger)
15% less cash boarding	100	$\beta_{B_{\text{TVM}}}$ $\beta_{B_{\text{cash}}}$	1.806 6.901	1.901 7.086
15% more cash boarding	100	$\beta_{B_{\text{TVM}}}$ $\beta_{B_{\text{cash}}}$	1.712 6.746	1.796 6.965

the right-hand-side variables on coefficient estimates ($\boldsymbol{\beta}_{B_{\text{cash}}}$ and $\boldsymbol{\beta}_{B_{\text{TVM}}}$) with sensitivity analysis. A B-cash value for each observation was randomly populated within the possible range. This procedure was achieved by setting the threshold as follows:

$$B_{\text{cash}} = \begin{cases} B_{\text{cash}} + \dfrac{\alpha}{|\alpha|} & \text{if } 0 < \mu < |\alpha| \\ B_{\text{cash}} & \text{otherwise} \end{cases} \tag{16}$$

where μ is a random number chosen between [0, 1] for each observation and α is the error range. The number of B-TVMs were then updated on the basis of new, randomly drawn B-cash.

The OLS model presented in Table 5 was then estimated to determine DT on the basis of the updated B-cash and B-TVM. Table 6 shows the upper and lower boundaries of the estimated coefficients $\boldsymbol{\beta}_{B_{\text{cash}}}$ and $\boldsymbol{\beta}_{B_{\text{TVM}}}$ after 100 iterations.

The effect of B-cash and B-TVM measurement error is evident in the ranges of estimates for $\boldsymbol{\beta}_{B_{\text{cash}}}$ and $\boldsymbol{\beta}_{B_{\text{TVM}}}$ and could therefore negatively affect the accuracy of DT predictions. As an example, $\boldsymbol{\beta}_{B_{\text{cash}}}$ is in the range of [6.7, 7.1]. For the worst-case scenario in which the number of onboard cash payers reaches its maximum (B-cash = 12), the resulting bias in DT estimation from a 15% measurement error in the right-hand-side variables is less than 4.8 s, which is only about 5% of the actual DT (91 s). The magnitude of bias in parameter estimates resulting from this GA estimation is thus considered acceptable.

CONCLUSIONS AND DISCUSSION

The DT has significant effects on transit reliability and operational efficiency. A practical modeling approach is needed to determine objectively and quantitatively the factors that contribute most to DT and can be supported with the availability of APC data in the majority of transit systems. Greater insights can be gained through more robust data sets to reveal the separate effects of fare payment structure, which empirically constitutes the major influence on DT. Although APC-AFC data sets offer ample amounts of information for transit performance analysis, the data fail to reflect the fare transactions that do not have electronic footage, which still account for a large portion of the fare payment structure in most transit systems. This failure thus imposes challenges in accurately estimating the effect on DT and hinders transit efficiency analysis for service optimization and performance assessment.

The analysis and proposed modeling approach in this paper showed that the gap in fare payment structure estimation might be remedied by treating the DT observations as an optimization problem. The GA was applied to the APC data set to classify the DT observations into behavior-controlled classes: BC, AC, and atypical scenarios. A combined modeling approach of GA and regression analysis was able to identify the fare payment structure (split of different payment types at the station level) and subsequently quantify their effects on DT. The modeling approach was implemented with data gathered along 35M BRT operated by UTA in Salt Lake City, serving as the pioneer BRT project, with several other BRT lines being planned in the near future. The route allows for several fare payment options and inspired this research given recent inquiries concerning the possible mass deployment of TVMs at every BRT station and their likely effectiveness in improving transit operational efficiency.

The final model for DT prediction showed an excellent goodness of fit with an adjusted R-square value of .90. Validity testing indicated that a possible estimation bias introduced by the GA estimation of some portions of the fare payment structure was relatively small. The model demonstrated the advantage of offboard fare collection over onboard fare collection, with average boarding times of 5.2, 1.8, and 6.9 s estimated for passengers using a smart card, prepaid pass, and onboard cash payment, respectively. Built environment and stop design also had effects on DT, as stations located on the median of the roadway were found to have a shorter DT and the ones located near shopping malls or hospitals tended to have a longer DT. The modeling approach is transferable to any transit routes or systems with access to the APC-AFC database and can help unveil why DT under certain conditions (time of day, station, passenger population, etc.) is likely to persist. The result of the model should not be the final word on the matter; rather it motivates the need for a next logical step: to provide guidelines and further analysis that are policy driven, such as fare evasion estimation, TVM cost–benefit analysis, and instructional guidance to facilitate a smooth boarding and alighting process, all of which are an effort to improve transit efficiency and reduce DT variation. The results can be potentially useful to future BRT projects. Additional analysis on more specific effects of the built environment is also needed and will require data that represent the range of common characteristics for these variables.

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The work presented in this paper remains the responsibility of the authors.

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CHAPTER 3

AN EFFICIENT GENERAL TRANSIT FEED SPECIFICATION (GTFS) ENABLED ALGORITHM FOR DYNAMIC TRANSIT ACCESSIBILITY ANALYSIS

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RESEARCH ARTICLE

An efficient General Transit Feed Specification (GTFS) enabled algorithm for dynamic transit accessibility analysis

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Abstract

The social functions of urbanized areas are highly dependent on and supported by the convenient access to public transportation systems, particularly for the less privileged populations who have restrained auto ownership. To accurately evaluate the public transit accessibility, it is critical to capture the spatiotemporal variation of transit services. This can be achieved by measuring the shortest paths or minimum travel time between origin-destination (OD) pairs at each time-of-day (e.g. every minute). In recent years, General Transit Feed Specification (GTFS) data has been gaining popularity for between-station travel time estimation due to its interoperability in spatiotemporal analytics. Many software packages, such as ArcGIS, have developed toolbox to enable the travel time estimation with GTFS. They perform reasonably well in calculating travel time between OD pairs for a specific time-of-day (e.g. 8:00 AM), yet can become computational inefficient and unpractical with the increase of data dimensions (e.g. all times-of-day and large network). In this paper, we introduce a new algorithm that is computationally elegant and mathematically efficient to address this issue. An open-source toolbox written in C++ is developed to implement the algorithm. We implemented the algorithm on City of St. George's transit network to showcase the accessibility analysis enabled by the toolbox. The experimental evidence shows significant reduction on computational time. The proposed algorithm and toolbox presented is easily transferable to other transit networks to allow transit agencies and researchers perform high resolution transit performance analysis.

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Introduction

Public transit accessibility is becoming an increasingly important topic among researchers and transit agencies for two main reasons. First, enhanced transit accessibility encourages multimodal and active transportation (i.e. walking and biking), and reduce personal vehicular trips. Consequently, it will lead to improved public health and reduction in green-house gas emissions [1–4]. Second, transit-dependent populations rely heavily on public transit for accessing essential services (e.g. job, school, health care, and grocery). Transit accessibility thus plays a critical role in achieving social equity [5–7]. Consequently, transit accessibility analysis can guide decision makings related to transportation investment and land use development [8].

Transit accessibility is defined as the ease of travel for an individual to reach a desired destination via public transit. Previous studies have identified several transit accessibility measures which can be categorized on the basis of whether travel time is taken into account. The *travel time discretionary* measures, which do not consider travel time, focus on service coverage, frequency, and comfort of service. However, overlooking the impact of travel time, which is a major contributing factor for evaluating the ease and feasibility of transit use, tends to overestimate the accessibility [9]. Consequently, the *travel time dependent* measures, accounting for the travel time between origin and destination on top of other miscellaneous factors (e.g. service coverage), have been gaining popularity in recent years [10]. Most of the relevant studies using the travel time dependent measures focused on transit accessibility for specific time-of-day (e.g. peak hour), yet ignored the temporal fluctuation in travel time throughout the day due to transit schedule variation [11]. The drawback for such analysis is that it might lead to an over-optimistic evaluation in transit accessibility due to the frequent service during peak hours. It is thus necessary to track such measures in both spatiotemporal dimensions.

Computing transit accessibility measure in spatiotemporal dimensions requires the calculation of travel time across all transit stations pairs at any given time-of-day. This process is computationally expensive and time consuming using the readily available commercialized software which makes it almost impossible for normal computers to perform [12]. Three main factors are causing this issue. First, the commercialized software packages often use high-level programming languages that increase the computation time. Second, the current algorithms used are developed to find the shortest path between any specific origin-destination (OD) pair [13]. Such algorithms will iterate until the shortest path is found between all OD pairs. Their efficiency thus degrades as network size grows. Third, the feasibility of transit trips from users' perspective is overlooked. The existing algorithms only minimize (instead of minimizing and limiting) the number of transfers, walking distance, and travel time when searching for the shortest path. Yet this may result in unrealistic routing. For example a route with 5 transfers and 2 mile walking distance is certainly not feasible for transit users. In addition, past research shows that over 90% of transit trips involve only one or two transfers [14].

The contributions of this paper are thus threefold. First, we introduce an innovative algorithm that can significantly decrease the computation required for calculating transit accessibility in both spatial and temporal dimensions. Second, we implement the algorithm in C++ and develop an open-source toolbox that will take advantage of open data (i.e. GTFS and census data) to track the patterns of various transit accessibility measures. Third, we identify the service gap through effective interpretation of the accessibility results.

The rest of the paper is structured as follows. We will review existing studies on transit accessibility and optimal path finding in transit network. This is followed by a brief description of GTFS data. *Methodology* section presents the proposed all-pairs shortest path algorithm design that is implemented in our toolbox to measure transit accessibility, as well as a discussion on travel time matrix construction and its influence on accessibility fluctuation. Then algorithm evaluation and accessibility interpretation are presented through an application demo using the St. George's transit network. Implications and conclusions are discussed at the end.

Literature review

Transit accessibility

Transit accessibility consists of two core elements: activity element and transportation element [15–16]. The activity element reflects the potential opportunities available at a destination and is usually measured by population density, job density, and/or service/facility availability at the destination. The transportation element reflects the ease of travel and is affected by the spatial and temporal coverage of transit, cost of travel (e.g. travel time), and comfort of service.

Several *travel time dependent* accessibility measures have been developed to date such as competition measures [17–19], constraints-based measures [18, 20–21], composite measures [22], cumulative and gravity-based measures [10–11, 23]. The latter two are the most widely used ones [24–29]. Cumulative measures are based on the number of potential opportunities to be reached within certain cost (e.g. travel time) threshold [20, 30–32], and can be expressed as:

$$A_{ic} = \sum_{j=1}^{J} B_{ij} * a_j \tag{1}$$

where A_{ic} is the cumulative accessibility measure at location i, a_j represents the potential opportunities at location j, and B_{ij} is a binary value, with 1 indicating that location j can be reached within a predetermined threshold (e.g. within 1-hour travel time window) and 0 otherwise. This measure assumes that a destination is reachable if and only if the impedance of reaching it is lower than the threshold. As a result, two destinations with the same potential opportunities would have the same impact on the measure as long as the impedance of reaching them are both within the threshold. Additionally, if the travel time to a desired destination is slightly outside the predetermined threshold, then this destination is deemed as inaccessible.

Gravity-based measures attempt to address this single-threshold deficiency by weighting the potential opportunities that can be reached based on a cost function (e.g. travel time) [20, 30, 33–34]. The general form is:

$$A_{ig} = \sum_{j=1}^{J} O_j * f(C_{ij}) \tag{2}$$

where A_{ig} is the gravity-based accessibility measure at location i, O_j is the potential opportunities at location j, and $f(C_{ij})$ is the impedance or cost function (e.g. travel time) for travelling between i and j via public transit. The main challenge of this method is the need of developing an impedance function between all OD pairs, other than estimating the number of potential opportunities at each location [35]. Gravity-based measure is able to account for spatial coverage, service frequency, destination attractiveness, and travel time between origins and destinations. By adding the temporal dimension to the gravity-based measure, it provides the most comprehensive picture of transit accessibility.

Weighted Average Travel Time (WATT) is in nature a gravity-based accessibility measure that weights travel times based on the attractiveness (potential opportunities) of destinations. According to Cao et al. [36], the WATT between stations can be described as:

$$WATT_i = \frac{\sum_{j=1}^{J} M_j * tt_{ij}}{\sum_{j=1}^{J} M_j} \tag{3}$$

where $WATT_i$ is the weighted average travel time of station i, also referred to as location indicator [37–38]. M_j is the potential opportunities (e.g. population density) of station j, tt_{ij} is the travel time (including egress, ingress, waiting, and transfer time) via public transit from station i to station j, and J is the total number of stations within transit network. WATT is based on gravity-like interaction pattern between locations [39]—increase in potential opportunity (gravity) and decrease in travel time (distance) will increase the accessibility (gravity force) between two stations (masses). WATT is intuitive to interpret. For example, $WATT_1$ = 60 minutes, indicates the average travel time from station 1 to all the other stations is 60 minutes. Calculating WATT for all time-of-day will provide a comprehensive transit accessibility measure that captures the temporal variation in services.

The major drawback of past studies, as Farber et al. [12] mentioned, is the missing piece of tracking the temporal fluctuation in travel time throughout the day due to computational intensity. This directly results in an over/under-estimation in transit accessibility [12, 14, 27, 40]. Farber et al. [12] reported that the calculation of travel time between all stations for all time-of-day for Salt Lake City network with 1,400 stations, and 100 transit routes would take approximately 60 days on a quad-core machine in ArcGIS.

Transit optimal path finding

Shortest path algorithms have been widely used in transportation to find the minimum travel time between OD pairs. The classic Dijkstra algorithm [41] finds the feasible path between given origin node to all destinations in an oriented graph. Later on, various speed-up techniques and algorithms have been developed to reduce the time complexity of the shortest path algorithm including heuristic algorithms [42–44], parallel computing [45], fuzzy algorithms [46–47], re-optimizing algorithms for dynamic networks [48], and timetable information system [49–51].

Within the context of public transit network, minimizing travel time is not the only objective of an optimal path. Instead, it is a multi-objective optimization problem that aims at minimizing travel time, number of transfers, walking distance, etc. Tan et al. [52] introduced reasonable paths finding algorithm (multi-objective) that constraints on travel time and walking distance. K shortest paths algorithms strive to address the multi-objective path finding problem by giving users the freedom to choose their desired path among several shortest (feasible) paths alternatives between a given OD pair [53–56]. However, both methods are only suitable when finding the shortest paths between a given OD pair. The optimal path finding algorithms (e.g. Dijkstra) are more efficient comparing with K shortest algorithms as they only generate one shortest path result. Time complexity of Thorup shortest path algorithm [57], as one of the fastest single-pair shortest path algorithms introduced for directed graphs with non-negative weights [58] to date, is $O(E + V \log(\log(V)))$, where E and V represent the number of edges (routes between each two consecutive stations) and vertices (stations), respectively. Yet the time complexity of single-pair shortest path algorithms increase significantly when implemented onto all OD pairs. All-pairs shortest path algorithm introduced by Pettie [44] has the time complexity of $O(EV + V^2 \log(\log(V)))$. The computation time grows as the network (number of stations and routes) expands. In addition, the edge weights are fixed and known in these algorithms. However, in transit network, the edge weight represents travel time between vertices, which changes throughout the day as the transit schedule and waiting time varies. Thus, an additional step of building the transit graph for each time-of-day is necessary for the all-pairs shortest path algorithm and for transit accessibility analysis.

GTFS

GTFS was created in 2005 by Google and TriMet for transit agencies to describe their schedules, trips, routes, and stops data in an open-source format that can be used for Google Transit Web-based trip planner. GTFS has evolved ever since based on the feedback from agencies and developers. To date, majority of transit agencies have made their GTFS data available to the general public (323 transit agencies nationwide) [59]. A GTFS dataset consists of several plain text files which have been formatted as Comma-Separated Values (CSV). In public transport network, stops represent transit stations where vehicles pick up and drop off passengers. Routes are sequence of two or more stops whose schedule is followed by a transit vehicle. Multiple trips can occur following the same route throughout a day. Therefore, a trip is a sequence of two or more stops that occurs at a specific time.

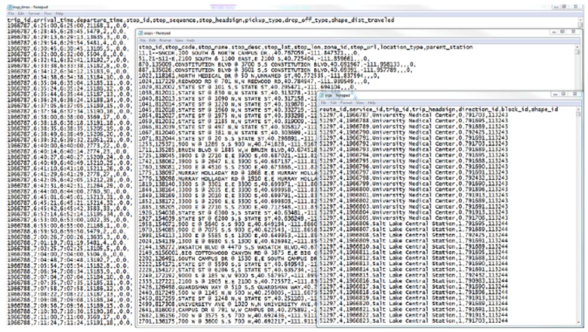

Fig 1. Stop-Times, stops, and trips files of GTFS for St. George, UT.

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Fig 1 shows a snapshot of GTFS Stops, Trips, and Stop-Times for the City of St. George's transit network. These files, combined with Calendar and Routes files contain detailed information about transit schedule for every minute of any day-of-week.

Previous studies presented examples on transit service evaluation using GTFS data, such as service area calculation, service coverage, time and distance service calculation, stop location and spacing optimization, service frequency, and span of service [60–62]. The scope of GTFS applications can be significantly expanded when combined with other datasets. For example, when jointly considered with Automatic Passenger Count (APC) data, GTFS can unveil important transit performance profile such as ridership-by-hour, by-trip, and by-stop, trip activity ranking, stop activity ranking, and activity-by-period. When combined with census data, GTFS might offer valuable information for transit connectivity and accessibility [12, 28, 63–65]. In this study, we will demonstrate such an example for travel time calculation using GTFS combined with census data.

Methodology

In this section, we will present our algorithm design for computing accessibility measures using GTFS data. The core component is the capability of finding the shortest path and updating the travel time between stations in both spatiotemporal dimensions. We further decipher the travel time matrix to explore the impact of network connectivity on accessibility measure. Fig 2 presents the overall methodological framework of this research including the core components (e.g. datasets, techniques, and formula) and their relations.

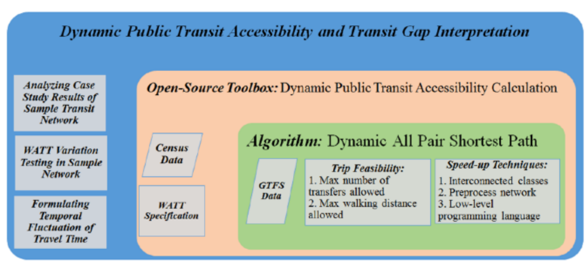

Fig 2. Methodological framework.

https://doi.org/10.1371/journal.pone.0185333.g002

Algorithm design

The proposed algorithm starts at each station by finding the next available trip passing through this station and the immediately connected stations at a specific time-of-day. These trips are further traced and travel times for stations met on these trips are updated. If the met stations are transfer stations (connected to a new route) then the next available trip on the new route is traced as well. This process continues until either all the stations in the network are met or the trips appear unpractical from users' perspective. All the calculation of travel times are based on the time-table reading from GTFS files, so there is no need to build the network graph for each departure time. We assume that any user is willing to take up to four transfers and walk up to 700 meters for transfers to reach a destination [66]. With this assumption, the algorithm is described as follows:

Step 1: Input data. The GTFS data is read into three classes including stops, routes, and trips. Stop class contains route and trip members that stores the passing routes and trip IDs. The route class includes stop member storing station IDs that are visited by the routes. The trips are stored in hash tables in order to improve the process of finding the next available trips.

Step 2: Find connected routes to each station and update travel time by walking. In this step, the distances between all stations are calculated and converted to travel time assuming a constant walking speed of 2.98 miles per hour [67]. The values are stored in a stop class member vector called travel time (tt_i). In addition, if a stop is in close vicinity of another stop within 700 meter radius that serves different routes, those routes will be added to route member and both stops will be added as connected stops member of stop class. The time complexity of this step is O (V^2).

It is important to mention that when a destination was not reachable within four transfers, the walking time between origin and destination stations was selected as the travel time. This prevents the WATT value from becoming extremely small or large considering the numerator in Eq (3). Specifically, the impact of travel time to reachable destinations will be undermined if a large travel time value is selected for non-accessible destinations. The walking time is used as travel time between origin and destination stations only in cases where transit travel time is longer than walking time and walking distance is less than 700 meters.

Step 3: Find all-pairs travel time and WATT for each station for all time-of-day. The pseudo-code for calculating all-pairs travel time for all time-of-day is shown in Fig 3. In the pseudo-code k represents the number of transfers allowed, *shortest path* function finds and updates the travel time from stop i (origin) to other stops that are connected to stop i without transfer, *shortest path T* function finds and updates the travel time from stop i (origin) to other stops that are connected to stop i with 1, 2, 3, and 4 transfers, respectively in each *k while loop*, t_o represents the earliest time to arrive at stop o from stop i and it is directly read from trips class, t represents the departure time from stop i, and t_o-t is the shortest path (travel time) from stop i to stop o.

As shown in Fig 3, the time complexity of proposed algorithm in Step 3 is $O(T^* V^* R^* S)$, where T represents number of time intervals, V is the total number of stations, R is the average number of routes available within four transfers of stations, and S is the average number of stations on each route. S–1 excludes the selected origin station from S. The time complexity of the algorithm then becomes $O(V^2 + T^* V^* R^* S)$. As the number of time intervals increases, V^2 becomes negligible comparing with $T^* V^* R^* (S-1)$. Therefore, the time complexity is nearly $O(TVRS)$.

Time complexity comparison. As mentioned in the *Literature Review* section, the fastest algorithm for time discrete all-pairs shortest path available to date was introduced by Pettie

```
For each time t ∈ T:                                  'T represents all departure times of day
{
        For each station i ∈ J:                       'J is total number of stations in transit network
        {
                TT = tt_i;                            'tt_i is the travel time vector from i to all other stations
                TS = Shortest Path (i, t);            'Shortest Path is shortest path function without transfer
                Set k = 0;
                While k < 4:
                {
                        TS = Shortest Path_T (i, t, TS);   'with transfer
                        k = k +1;
                }
                Calculate and store WATT_it;
        }
}
Shortest Path (i, t):
{
        Set vector <pair (stop, time)> TS = empty;
        For each route m ∈ CR_i:                      'CR_i is connected routes of station i
        {
                Find closest trip n on route m;
                Find arriving time t_o at stops o ∈ n;
                For each o ∈ n:
                        If t_o − t < TT_o:
                                TT_o = t_o − t;
                        If o is a transfer stop:
                                Store pair of o and t_o in TS;
        }
        Return TS;
}
Shortest Path_T (i, t, TS):
{
        TS1 = TS;
        Set vector <pair (stop, time)> TS = empty;
        For each pair of o and t_o ∈ TS1:
        {
                For each route m ∈ CR_tr:             'CR_tr is connected routes of transfer stops in TS1 vector
                {
                        Find closest trip n on route m;
                        Find arriving time t_o at stops o ∈ n;
                        For each o ∈ n:
                                If t_o − t < TT_o:
                                        TT_o = t_o − t;
                        If o is a transfer stop:
                                Store pair of o and t_o in TS;
                }
        }
        Return TS;
}
```

Fig 3. Pseudo-code for finding all-pairs shortest path and station WATT through a day.

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[44] and has a time complexity of $O\,(EV + V^2\,log\,(log\,(V)))$. Implementing Pettie's algorithm onto time-dependent network will result in time complexity of $O\,(TEV + TV^2\,log\,(log\,(V)))$. In order to compare the time complexity of proposed algorithm with Pettie's algorithm, the $O\,(TVRS)$ must be compared with $O\,max\,(TEV,\,TV^2\,log\,(log\,(V)))$. As a result, if one of the statements in Eqs (4) and (5) holds true, then our proposed algorithm have lower time complexity than Pettie's.

$$TVRS \leq TEV \rightarrow RS \leq E \tag{4}$$

$$TVRS \leq TV^2\,\log(\log(V)) \rightarrow RS \leq Vlog(\log(V)) \tag{5}$$

Proof of Eq (4):

R represents the average number of routes available within four transfers of stations. Consequently, the maximum value for R equals to the total number of available routes in the network. E is the total number of routes connecting two consecutive stops and $E = R_{max} * S$. Thus, $R * S \leq E$ always holds true. It is therefore evident that the time complexity of the proposed algorithm is lower than Pettie's. As the transit network size grows, the ratio of $\frac{R_{max}}{R}$ will increase. This indicates that with the increase of number of nodes and edges in time dependent all-pairs shortest path problem, the time complexity of Pettie's algorithm increases at a faster rate than that of our proposed algorithm. The computational performance is verified in the *Application* section where the algorithm is tested on an actual transit network.

WATT

As mentioned in *Literature Review*, WATT is an accessibility measure that weights travel time based on the potential opportunities of destinations. Since the potential opportunities available at each destination is assumed constant throughout the day, a closer look of travel time matrix can provide valuable insights on WATT fluctuation. Assume $k_{0i}, k_{1i}, k_{2i}, k_{3i},$ *and* k_{4i} represent sets of stations (destinations) reachable from station i by taking 0, 1, 2, 3, and 4 transfers, respectively. $k_{non-reachable\ i}$ is the set of stations that cannot be reached by taking 4 transfers from station i. Then the travel time from station i to any given station in k_{0i} at time-of-day t will be:

$$tt_{ij_t} = WT_{0_t} + \frac{d_{ij}}{OS_0}, \quad j \in k_{0i} \tag{6}$$

where tt_{ij_t} is the travel time from station i to j at time t, WT_{0_t} is the waiting time at station i for the connecting route at time t, d_{ij} is the distance between station i and j, and OS_0 is the operating speed of the connecting route. Similarly, the travel time from station i to any given station in k_{1i} at time-of-day t becomes:

$$tt_{ij_t} = WT_{0_{ct}} + \frac{d_{ic}}{OS_{0c}} + WT_{1_{t+ct}} + \frac{d_{cj}}{OS_1}, \quad j \in k_{1i} \tag{7}$$

where c represents transfer station on travel routes from i to j, $WT_{0_{ct}}$ is the waiting time at station i for the connecting route between i and c at time t, d_{ic} is the distance between station i and c, OS_{0c} is the operating speed of the connecting route between i and c, $WT_{1_{t\ ct}}$ is the waiting time at station c for the connecting route between c and j at time $t+ct$, d_{cj} is the distance between station c and j, and OS_1 is the operating speed of the connecting route between c and j. ct is the travel time from station i to c, and is equal to $WT_{0_{ct}} + \frac{d_{ic}}{OS_{0c}}$.

Eq (7) can be further expanded as follows to find the travel time from station i to any given station in $k_{2i}, k_{3i},$ *and* k_{4i}:

$$tt_{ij_t} = WT_{0_{c_1 t}} + \frac{d_{ic_1}}{OS_{0c_1}} + WT_{1_{t+c_1 t}} + \frac{d_{c_1 c_2}}{OS_{1c_2}} + WT_{1_{t+c_1 t+c_2 t}} + \frac{d_{c2j}}{OS_2}, \quad j \in k_{2i} \tag{8}$$

$$tt_{ij_t} = WT_{0_{c_1 t}} + \frac{d_{ic_1}}{OS_{0c_1}} + WT_{1_{t+c_1 t}} + \frac{d_{c_1 c_2}}{OS_{1c_2}} + WT_{1_{t+c_1 t-c_2 t}} + \frac{d_{c_2 c_3}}{OS_{2c_3}} + WT_{1_{t-c_1 t+c_2 t-c_3 t}} + \frac{d_{c_3 j}}{OS_3}, \quad j \in k_{3i} \tag{9}$$

$$tt_{ij_t} = WT_{0_{c_1 t}} + \frac{d_{ic_1}}{OS_{0c_1}} + WT_{1_{t+c_1 t}} + \frac{d_{c_1 c_2}}{OS_{1c_2}} + WT_{1_{t+c_1 t+c_2 t}} + \frac{d_{c_2 c_3}}{OS_{2c_3}} + WT_{1_{t-c_1 t+c_2 t+c_3 t}} + \frac{d_{c_3 c_4}}{OS_{3c_3}} + WT_{1_{t-c_1 t+c_2 t+c_3 t-c_4 t}} + \frac{d_{c_4 j}}{OS_4}, \quad j \in k_{4i} \tag{10}$$

where indices c_1, c_2, c_3, *and* c_4 represent first, second, third, and fourth transfer stations, respectively. Assuming that operating speed of routes does not change throughout the day, then the average travel times from station i to any other station become:

$$Average\ tt_{ij} = \frac{\sum_{t=0}^{T} WT_{0_t}}{n} + \frac{d_{ij}}{OS_0}, \quad j \epsilon k_{0i} \tag{11}$$

$$Average\ tt_{ij} = \frac{\sum_{t=0}^{T} WT_{0_{ct}} + WT_{1_{t+ct}}}{n} + \frac{d_{ic}}{OS_{0c}} + \frac{d_{cj}}{OS_1}, \quad j \epsilon k_{1i} \tag{12}$$

$$Average\ tt_{ij} = \frac{\sum_{t=0}^{T} WT_{0_{c_1 t}} + WT_{1_{t+c_1 t}} + WT_{1_{t+c_1 t+c_2 t}}}{n} + \frac{d_{ic_1}}{OS_{0c_1}} + \frac{d_{c_1 c_2}}{OS_{1c_2}} + \frac{d_{c2j}}{OS_2}, \quad j \epsilon k_{2i} \tag{13}$$

$$\begin{aligned} Average\ tt_{ij} = {} & \frac{\sum_{t=0}^{T} WT_{0_{c_1 t}} + WT_{1_{t+c_1 t}} + WT_{1_{t+c_1 t+c_2 t}} + WT_{1_{t-c_1 t+c_2 t+c_3 t}}}{n} + \frac{d_{ic_1}}{OS_{0c_1}} + + \frac{d_{c_1 c_2}}{OS_{1c_2}} \\ & + + \frac{d_{c_2 c_3}}{OS_{2c_3}} + + \frac{d_{c_3 j}}{OS_3}, \quad j \epsilon k_{3i} \end{aligned} \tag{14}$$

$$\begin{aligned} Average\ tt_{ij} = {} & \frac{\sum_{t=0}^{T} WT_{0_{c_1 t}} + WT_{1_{t+c_1 t}} + WT_{1_{t+c_1 t+c_2 t}} + WT_{1_{t+c_1 t-c_2 t+c_3 t}} + WT_{1_{t-c_1 t+c_2 t+c_3 t-c_4 t}}}{n} + \frac{d_{ic_1}}{OS_{0c_1}} \\ & + \frac{d_{c_1 c_2}}{OS_{1c_2}} + \frac{d_{c_2 c_3}}{OS_{2c_3}} + \frac{d_{c_3 c_4}}{OS_{3c_3}} + \frac{d_{c_4 j}}{OS_4}, \quad j \epsilon k_{4i} \end{aligned} \tag{15}$$

where n is the total number of departure times (t) that travel time is calculated between i and j, and T is the last departure time. As it shows in Eqs (6) through (15), the fluctuation on travel time from station i to other stations is predominantly determined by the waiting time variation at different times-of-day. Each additional transfer taken to reach destinations will add an extra transfer waiting time and in-vehicle time. Thus, the stations that are connected to rather higher number of routes (more stations in set k_{0i}) are likely to have lowered average travel time to destinations. In addition if the stations in set k_{0i} have relatively higher potential opportunities available, then station i would have better WATT. For an average station i, the size of sets k_{0i}, k_{1i}, k_{2i} are smaller in low connectivity network than highly connected networks. This shows the importance of route (network) connectivity on network travel time and accessibility.

Application

The algorithm developed in this paper is tested onto the City of St. George transit network operated by SUNTRAN in the State of Utah. In this section, we present a brief description of SUNTRAN transit network, followed by algorithm efficiency assessment and transit accessibility results.

Study network: SUNTRAN network

St. George is a small-sized city located in Southern Utah with a population of 76,817. Census block data for the State of Utah in 2015 have been collected from the Utah Automated Geographic Reference Center (AGRC) website [68] also available in S1 Dataset. Census block is the smallest geographic unit used by United States Census Bureau for tabulation of data collected from all houses. The high resolution of census block data ensures the accuracy of accessibility measures. The data were used to calculate the population within a 700-meter radius of each transit station to represent the potential opportunity offered by that station. The GTFS

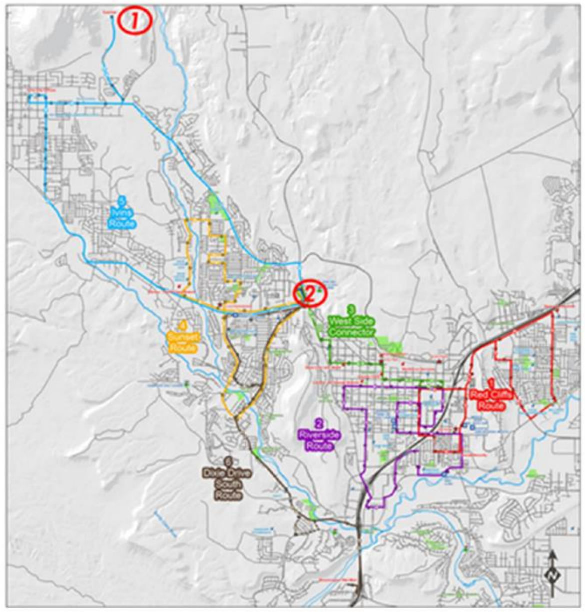

Fig 4. SUNTRAN's transit network map; ***1: Taucahn Station, 2: Sunset Corner Station.***

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data for St. George transit network operated by SUNTRAN were retrieved from GTFS data exchange website [69]. SUNTRAN's transit network consists of six bus routes and 134 bus stops. Four of these routes operate at 40-minute fixed headway and the other two operate at 80-minute fixed headway. Fig 4 shows SUNTRAN's transit network map. The two stations highlighted in Fig 4 are used for micro-level analysis of transit accessibility.

Other than using the population density within 700-meter radius of stations to represent the potential opportunity, all-pairs shortest paths for each time-of-day are needed to calculate the travel time component of WATT. This is completed using the GTFS data via the developed algorithm presented in Fig 3.

Algorithm efficiency

To validate the computational efficiency of the proposed algorithm, we compared our algorithm against Pettie's algorithm. Both algorithms for time dependent all-pairs shortest path search were coded in C++. In addition, the computation time using Esri's ArcMap Network was estimated. All calculations were performed using a desktop computer with an Intel® Core™ i7-4790 3.6 GHz computer processor and 16 GB of RAM. The results of this computation experiment are shown in Table 1. It indicates that even for a relatively small-sized network where $R \sim Rmax$, the proposed algorithm outperforms Pettie's algorithm. This is probably due to the necessity of rebuilding the network graph for each time interval as an additional step in Pettie's algorithm. The Esri's ArcMap Network Analyst, the most commonly used commercial software package for spatial analysis, is more than three times slower than our

Table 1. Computational time for time dependent all-pairs shortest paths in SUNTRAN's transit network.

SUNTRAN transit network, St. George	
No. of stations	134
No. of routes	6
No. of Origin-destination pairs	17822
WATT computation time (for five minute interval from 5 AM to 8 PM)	
Uniquely computed shortest path = 17822 * 181 = 3,225,782	
Proposed algorithm	210 Seconds
Pettie's algorithm	273 Seconds
Esri ArcMap Network Analyst	672 Seconds

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proposed algorithm. We expect that the proposed algorithm perform even better as the network size grows and are exploring it in an ongoing study. The algorithm was implemented in Fayyaz et al. [64] to compute dynamic transit accessibility for the entire Utah Transit Authority's (UTA) network. UTA's network consists of 6,265 transit stations and 125 transit routes including commuter rail, light rail, bus rapid transit, and bus. The WATT was measured for all stations every 10-minute interval from 4 AM to 10 PM (4,239,024,300 unique shortest paths). Fayyaz et al. [64] has reported that the total computation time was less than 6 days whereas the same calculation in Esri's ArcGIS would take up to 165 days.

WATT results and transit accessibility analysis

WATT was calculated for all stations for every 5-minute interval from 5 AM to 8 PM throughout a typical weekday. Fig 5 shows the average, maximum, and minimum WATT result for each station within the network. Note that the WATT values are conglomerated based on station ID, with high WATT representing low accessibility and vice versa. This is due to the fact that station IDs are labeled sequentially for stations along the same route in St. George's network.

WATT was further plotted against the population within 700-meter radius of each station and the result is shown in Fig 6. A station that have low accessibility value (a.k.a. high WATT) and low population in the vicinity does not raise too much concern. Yet problem arises at stations with high accessibility (a.k.a. low WATT) and low population or at stations with low

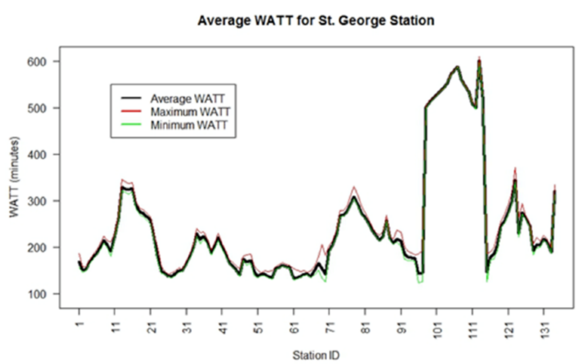

Fig 5. WATT plotted regarding station ID.

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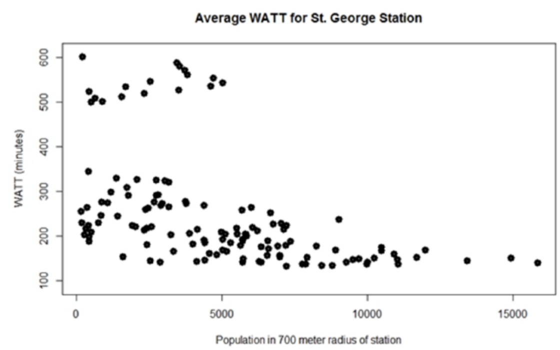

Fig 6. WATT plotted regarding the station population living in 700 meter radius.

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accessibility (a.k.a. high WATT) and high population. In the first scenario, redundancy exists in the current transit network with very scarce demand which results in network inefficiencies and waste of resources. In the second scenario, demand exceeds supply leading to customer dissatisfaction and inequitable access. The stations fall into the second scenario are highlighted with red circle in Fig 6. These stations should be given top priority for improved transit service. The stations with excess supply (first scenario) are highlighted with green circle. These stations must be studied under a closer scrutiny to further justify their existence. Removal of these stations might be necessary in case of budget constraint. To better capture the equity issue, socioeconomic characteristics of the population around the stations can be considered for a better result filtration. Unfortunately, for the City of St. George, the variation of socioeconomic characteristics (i.e. age, gender, average salary) across different transit stations is insignificant, impeding the equity analysis.

To better illustrate the temporal fluctuation of WATT, two stations were chosen for micro-level analysis, including Tuacahn station and Sunset Corner station with highest and lowest WATT values respectively (Figs 7 and 8). Tuacahn station (marked in Fig 4) is located in recreational area with a population of 20 people living within the 700-meter radius. Bus route 5 is

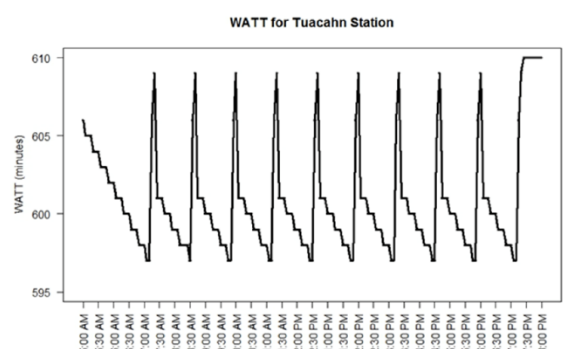

Fig 7. Temporal fluctuation in WATT for Tuacahn station.

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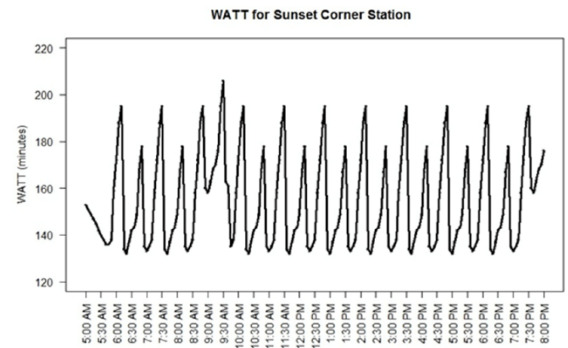

Fig 8. Temporal fluctuation in WATT for Sunset Corner station.

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the only bus serving the station that operates on an 80-minute headway. On the contrary, Sunset Corner station is located close to shopping centers and residential areas with 1,600 people living within the 700-meter radius. Bus routes 3, 4, 5, and 6 are serving this station. As shown in Fig 7, due to its geographical remoteness and scarce transit service, the accessibility of the Tuacahn station reaches its maximum (lowest WATT) when the bus is at the station and goes back to minimum right after it departs (highest WATT). Transit accessibility then will gradually increase as the next bus is approaching. The time interval between the two consecutive peak points is equal to 80 minutes (operating headway of the serving route). The accessibility of the station would not be improved significantly (with a marginal 10 to15-minute difference in WATT) even when the bus is at station due to its remote location. On the other hand, Sunset Corner station is located in close vicinity of the city center and served by four transit routes. Fig 8 shows that the time interval between the two consecutive peak points for this station varies between 15 to 30 minutes. This difference is dependent on the coordination between the four routes serving the station. Fig 8 indicates that the coordination between the four routes at Sunset Corner station is at worst condition around 9:35 AM. This is due to the unavailability of service from Route 5 at that hour for the station.

To better interpret WATT's implications, we present a simple network consisting of one transit route and three transit stations. The route is operating on a 25-minute headway. Route's timetable is shown in Fig 9 representing route departure time at each station and direction. The impact of station's geographical location can be captured by comparing WATT of the three stations, given that all of them are served by the same route.

Fig 10A shows the WATT variation throughout the day for all three stations. Station No. 1 has the worse WATT since it requires the longest distance (travel time) to reach potential opportunities. The poor accessibility of Station No. 1 is caused by geographical disadvantage, which is demonstrated in the higher WATT values compared to Stations No. 2 and No. 3. Fig 10B shows the sensitivity analysis of WATT for Station No. 1 in response to changing headways. Note that since only one route is in service, the waiting time will always increase abruptly the moment that bus departs from the station, which is manifested in Fig 10B as pulses (WATT changes from minimum to maximum). Also note that the decreasing slope of WATT is always constant. This is caused by gradual reduction in waiting time and consequently gradual reduction in travel time and WATT. Thus, the route headway will determine the time lag between local minimum and maximum WATTs, and consequently, the range of WATT

Blue Route Map & Time Table

Stop 1	Stop 2	Stop 3
70	50	35
95	75	60
110	90	85
145	125	110

Stop 1	Stop 2	Stop 3
35	55	70
60	80	95
85	105	120
110	130	145

Fig 9. Representation of a simple transit network.

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fluctuation. Fig 10C shows the varying effects of route's operating speed on WATT. The headway is kept same (25-minute), and consequently the time lag between local WATT maximum and minimum is the same across all three scenarios. The operating speed, as can be observed, directly affects the local minimum WATT. Faster service shortens travel time, thus people can reach their destinations quicker, and the local minimum WATT (when waiting time is zero) decreases.

Building upon the sample network shown, an extra station (Station No. 4) and an extra route (Red route) are added and shown in Fig 11. Three different scenarios were developed to demonstrate the influence of incoordination and headway differences between Blue and Red routes on Stations No. 1, 3, and 4's WATT. In scenario 1, both routes are operating on the same headway (25 minutes) and same initial bus departure time. In scenario 2, both routes are operating on the same headway (25 minutes) but the first bus of Red route departs 5 minute later than the first bus of Blue route. In scenario 3, the initial bus departure time of both routes are the same, but their headways differ (25 minutes for Blue route and 15 minutes for Red route). The different departure time in scenario 2 leads to 5-minute more waiting time for traveling from Station No. 1 to Station No. 4 comparing with scenario 1. This can be seen in Fig 12A as the WATT difference (y-axis) between the two scenarios. However, this departure time difference has a positive effect on WATT of Station No. 4 (Fig 12C), since it enables faster access to Station No. 3 and have no effect on waiting time to reach Stations No. 1 and 2. Thus, the incoordination of routes increases travel time and WATT in one direction and decreases travel time and WATT in other direction. This also indicates that there exists an optimum coordination which will minimize the sum of WATTs throughout the day on both directions.

Finally, the impact of headway differences between Blue and Red routes is reflected in scenario 3. Comparing scenario 3 with scenarios 1 and 2, it shows that lower headway of red route generally decreases travel time and WATT throughout the day. However, the extent of

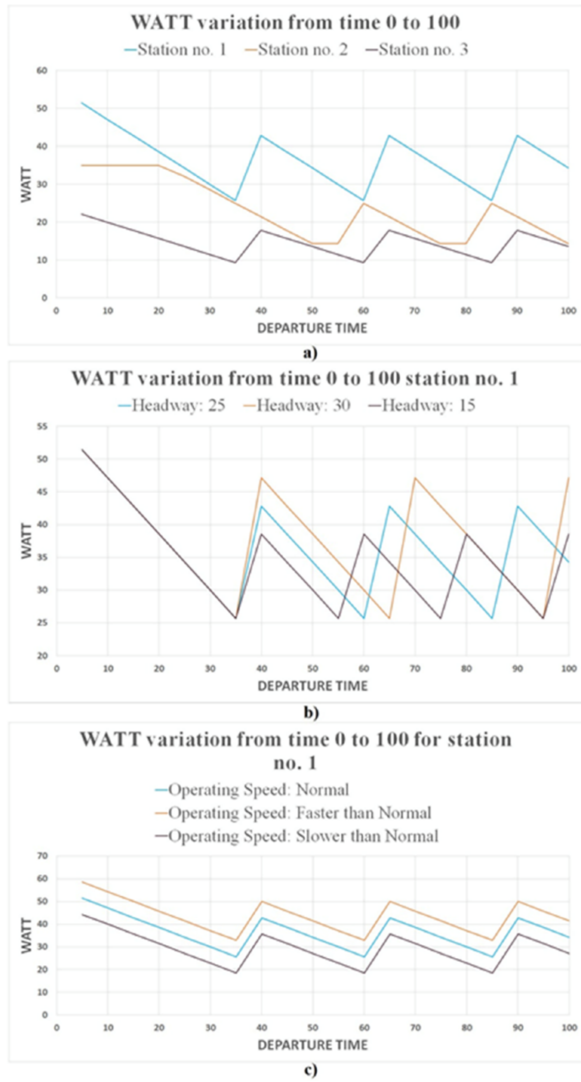

Fig 10. WATT variation throughout the day. (A) Stations no. 1, 2, and 3, (B) different headways, (C) different operating speed.

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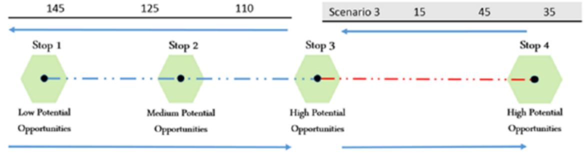
reduction on WATT varies for different stations. Station No. 4 is experiencing the highest reduction in WATT. Station No. 4 relies on Red route to reach all other stations in the network. As a result, lower headway of Red route will result in lower wait time and WATT. Note that only scenario 3 demonstrates the inconsistence in local minimum/maximum WATT, due

Blue Route Map & Time Table

Stop 1	Stop 2	Stop 3
70	50	35
95	75	60
110	90	85
145	125	110

Red Route Map & Schedule Scenarios with Headway and First Trip Timetable

First Trip	Headway	Stop 3	Stop 4
Scenario 1	25	45	35
Scenario 2	25	50	40
Scenario 3	15	45	35



Stop 1	Stop 2	Stop 3
35	55	70
60	80	95
85	105	120
110	130	145

First Trip	Headway	Stop 3	Stop 4
Scenario 1	25	35	45
Scenario 2	25	40	50
Scenario 3	15	35	45

Fig 11. Simplified network with two routes.

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to the varying waiting times for transfer between routes. The WATT graphs can be used to adjust the transit service coordination such that the local minimum WATT can occur when the demand is high.

Based on the above analysis, the WATT pattern shown for the St. George network can be better deciphered. Revisiting Figs 7 and 8, it shows that Tuacahn station is geographically disadvantaged as demonstrated by the high global maximum WATT. The long headway (80 minutes) of Tuacahn station (Fig 7) leads to the large range of WATT, as a result the local maximum WATT almost reaches the station's global maximum. The operating speed of the serving route is also rather slow since the local minimum WATTs are only 13 minutes less than global maximum WATT. There is no headway differences in the network as all the routes are operating at 40 or 80 minute fixed headway. Thus, there is no differences between local maximum (minimum) WATTs.

The headway for Sunset Corner station (Fig 8) is affected by arrival time of buses operating on the several routes serving this station. As a result, the time lag between to local maximum (minimum) WATTs is shorter than 40 minutes due to the overlapping effect. Sunset Corner station's WATT variation has a similar pattern as Fig 12B scenario 2. In such cases, the local maximum WATTs are not always reached momentarily due to bus departure. The local minimum WATTs are consistent throughout the day indicating that the routes serving the station are providing almost the same operating speed to potential destinations since different local minimums are caused by different routes (or combination of them). The local minimum WATTs are much smaller than global maximum WATTs in Fig 8 (in order of 85 minutes), indicating that the serving routes (or combination of them) are operating on rather high speeds.

The WATT pattern of stations in St. George network is repetitive throughout the day. This is caused by the fact that limited number of routes (6) are operating on fixed headways that are 40-minutes or its multiple (80 minutes). In bigger networks, the WATT pattern analysis will become more complex and it can better show temporal deficiencies of service. We believe the station-level WATT graph is a powerful tool for public transit agencies and planners in conducting microscopic transit performance analysis. It not only captures transit service performance measures such as headway, operating speed, coordination, and travel time, but also associates them with land use and potential opportunities available (geographic distribution of attractiveness).

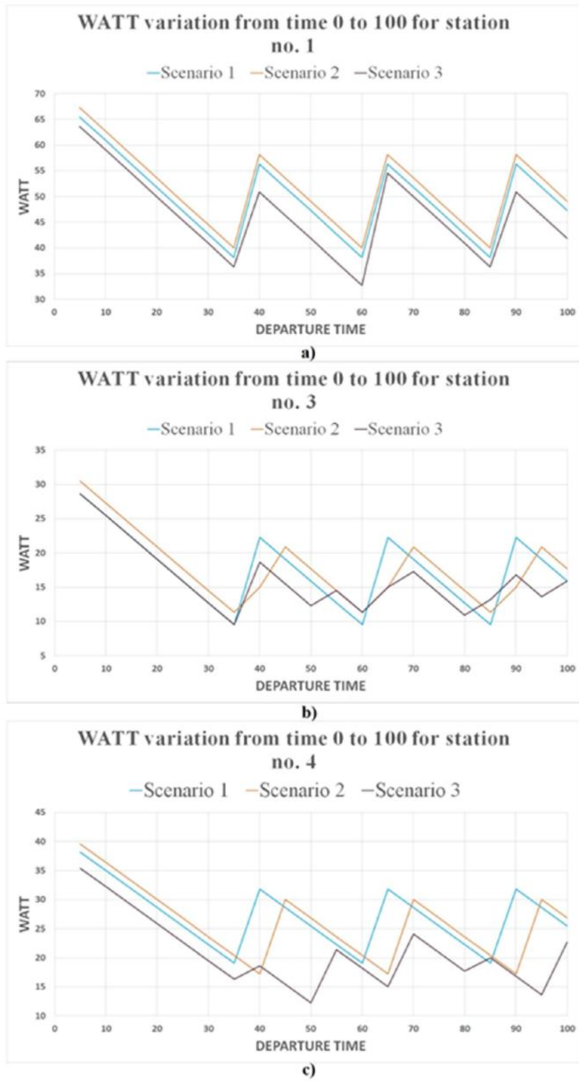

Fig 12. WATT variation throughout the day in three scenarios. (A) Station no. 1; (B) station no. 3; and (C) station no. 4.

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Conclusion

Public transit accessibility has been studied for many years in evaluation of transit services. However, the time-dependent transit accessibility has not been explored much until recently, due to the unavailability of transit schedule data. The introduction of GTFS greatly facilitates such analysis by offering high resolution transit schedule data in a standard format.

Existing research acknowledged that transit accessibility measures that capture the spatio-temporal patterns are most helpful for analyzing the gap in transit services. Yet the computational efficiency is challenging for all the OD pairs within the transit network. We introduce an efficient and innovative algorithm to solve this issue and prove that it has lower time complexity ($O(V^2 + TVR(S-1))$) compared to the fastest shortest path algorithm to date ($O(TEV + TV^2 \log(\log(V)))$. The proposed shortest path algorithm limits the number of transfers for each transit trip to four. This constraint not only makes the result more realistic but also improves time complexity and speed of the algorithm significantly.

The proposed algorithm is implemented in C++ and utilizes the publically available datasets including GTFS and Census data. The methodology is applied to SUNTRAN's transit network in City of St. George, UT. The result shows that our proposed algorithm outperforms other widely used all-pairs shortest-path algorithms/packages, including Petti's and Esri's ArcMap Network Analyst. This difference will grow exponentially as network expands since the difference between the number of routes connected within 4 transfers will become much less than total number of routes of the network. For example, a simple estimation of computation time for a large-size network with 6,200 stops and 125 routes for every 10-minute of the day from 4 AM to 10 PM is approximately 5.2 days for our proposed algorithm and 165 days for Esri's ArcMap Network Analyst. Another contribution of this paper is the introduction of the analysis method for interpreting transit accessibility. The macro-level analysis on WATT is effective in identifying stations with excessive supply or demand. The micro-level analysis can be used for tracking the temporal fluctuation of accessibility and identifying inefficiencies in bus coordination/scheduling.

Future research will focus on incorporating socioeconomic characteristics, travel patterns, and apply the methodology to a larger network. For example, the average income of population living in the vicinity of transit stations can be used as a surrogate for prioritizing public transit investments. The potential opportunities component of WATT aims to weight travel time based on the attractiveness of the destinations. Such weighing function and consequently the PTA results can be further enhanced by considering the travel pattern of transit users [70–72]. Implementing the framework to a larger network (more routes and stations) with both fixed and variable headway routes will provide better insights on the data management capability of the toolbox and showcase the temporal trends in network coordination. Finally, future expansions of the algorithm can benefit from adding several multimodal options for ingress and egress to transit stations such as park-and-ride and cycling.

Supporting information

S1 Dataset. GTFS for upload.
(ZIP)

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Writing – original draft: S. Kiavash Fayyaz S.

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CHAPTER 4

DYNAMIC TRANSIT ACCESSIBILITY AND TRANSIT GAP CAUSALITY ANALYSIS

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Dynamic transit accessibility and transit gap causality analysis

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ABSTRACT

Public Transit Accessibility (PTA) analysis helps transit agencies and planners identify areas in need of transit service improvements and prioritize transit investments. To evaluate the accessibility of existing transit services and identify access gaps, it is critical to accurately estimate travel times between transit stops, which change throughout the day due to transit schedule variations. Commonly used methods in PTA ignore such temporal fluctuation. Moreover, these methods are unable to elucidate the causes of poor PTA. To address these issues, we first implemented an algorithm to effectively compute travel times at multiple departure times throughout the day in order to enable spatiotemporal PTA analysis. A series of indicators that are intuitive to interpret were developed to determine the varying causes of poor PTA and identify areas with immediate needs for improvements. We showcase the analytical framework using a transit network in the State of Utah operated by the Utah Transit Authority. The analysis is based solely on publicly-available open datasets, which makes it generally adaptable to other transit networks. Results can assist transit agencies with identifying areas in need of service improvement and prioritizing future investments.

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1. Introduction

Public Transit Accessibility (PTA), a key indicator of transit service quality, plays an important role in users' mode choices (Moniruzzaman and Paez, 2012). PTA directly affects transit ridership and, consequently, influences active transportation mode use, public health, and other characteristics of the urban environment (Farber and Páez, 2011; Litman, 2003). The social functions of urbanized areas are highly dependent on and supported by convenient access to public transportation systems, particularly for the less privileged populations with limited auto ownership. Poor PTA can cause social exclusion for disadvantaged populations (SEU, 2003). An effective understanding and evaluation of PTA is therefore necessary to help transit agencies identify areas in most need of improvement and guide investment decisions and land use development (Coffel, 2012).

PTA refers to the ability to reach goods, services and activities via public transit. By definition, PTA has two main components: activity and transportation (Burns, 1980; Koenig, 1980). The activity component describes the attractiveness of destinations and is usually measured by population density, job density, and/or facilities available at destinations. The transportation component measures the ability to reach destinations and is influenced by spatiotemporal coverage of services, travel cost (e.g. travel time), and the comfort of service as experienced by users. It is difficult for any single PTA analysis to consider all factors that potentially affect the ease of travel. Ignoring critical factors, however, will result in the over- or underestimation of PTA. Travel time is one of the critical factors reflecting the feasibility of transit use. Overlooking travel time tends to overestimate the portion of population with transit access (Polzin et al., 2002). As a result, *travel time dependent* PTA measures, such as cumulative and gravity-based accessibility measures, have been widely used in recent years (El-Geneidy et al., 2016; Foth et al., 2013; Lei and Church, 2010; O'Sullivan et al., 2000; Widener et al., 2015).

Most relevant studies (Benenson et al., 2010; Krizek et al., 2009; Mavoa et al., 2012; Owen and Levinson, 2012) on transit performance have focused on transit travel time for a specific time-of-day (e.g. peak hour). This leads to an overly optimistic evaluation, as the optimum transit services (e.g. highest frequency and largest geographic coverage) are usually provided in peak periods. PTA could be measured for several times-of-day to unveil the temporal fluctuation in transit services (Farber and Fu, 2016; Farber et al., 2016), but analyzing and interpreting the results can be challenging due to the complexity of the added temporal dimension. Past studies in PTA have concentrated on identifying areas with poor accessibility (Benenson et al., 2010; Krizek et al., 2009; Mavoa et al., 2012; Owen and Levinson, 2012; Owen and Levinson, 2015) or mismatches between transit services (supply) and the Need for Public Transit Services (NPTS) (demand) (Farber et al., 2016; Fransen et al., 2015). However, little has been done with regard to identifying the causes of poor PTA in order to inform transit investment decisions. There are two main causes leading to poor PTA:

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inefficient transit services (e.g. inadequate spatial/temporal coverage), and geographical disadvantage (e.g. long distances between the study area of interest and desired destinations). Poor PTA due to inadequate transit services can be remedied by a transit agency via transit investment. However, a remote area with good transit services may still experience poor PTA. There is not much a transit agency can do in this latter case other than play one part of much broader land development efforts. There is therefore a critical need for PTA analysis to reflect both causes and distinguish between the two to avoid making poor investments in the wrong sets of solutions. To address this issue the transit gap causality analysis is required. Transit gap causality analysis measures how large the gap between PTA and NPTS is, and whether the gap is fixable by transit agencies. Dynamic PTA analysis, considering spatiotemporal dimensions with finer resolution, offers greater insights into the various causes of poor accessibility. This study complements the existing literature by developing effective indicators that provide a fuller exploration of PTA variation and transit gap causes in order to guide future transit investments.

The contribution of this paper is fourfold. First, this study captures the temporal fluctuations of PTA by measuring travel time at multiple departure times throughout the day. The time resolution is selected in such a way to reflect all possible waiting times and schedule variations. Weighted Average Travel Time (WATT) is utilized as a gravity-based PTA measure to showcase the spatiotemporal PTA analysis in high resolution at the transit stop-level. Second, we introduce a unified ratio that can fully capture the spatiotemporal variability and quality of transit services throughout the day and is robust to parameter or scale selection. Third, the concept of Public Transit Accessibility Gap (PTAG) is developed to identify regions with transit mismatches by comparing WATT to the Need for Public Transit Services (NPTS). Finally, PTAG and the unified ratio are jointly used to identify the causes of transit mismatches and poor PTA. The results rank areas based on their need for transit improvement to further inform transit investment decisions.

Previous studies on PTA are discussed at length in Section 2. We demonstrate that these previous studies lacked the ability to accurately analyze the temporal aspect of PTA and fully reveal the causes of accessibility gaps due to the lack of computational methods that enable the spatiotemporal analytics to uncover transit supply and demand interaction. Then, the analytical framework for measuring PTA and identifying accessibility gaps is presented via the development of indicators that reflect transit gap causes while ensuring effective geographic standardization. The analytical framework is applied to the Utah Transit Authority (UTA) transit network in the State of Utah. The paper concludes with a discussion of results and implications of study findings.

2. Literature review

Accessibility analysis links land-use with transportation (Horner, 2004). The land-use part of the analysis seeks to quantify the activity component of accessibility based on desired urban/rural services that are available. The transportation part of the analysis characterizes the ease of travel, and is usually described with a cost function. Several measures have been developed to date for PTA. The cost function is an important factor that distinguishes these measures (Lei and Church, 2010). Some of them, such as local index of accessibility (Rood and Sprowls, 1998), percentage of service coverage (Kittelson et al., 2003), and transit level-of-service (Ryus et al., 2000; Tumlin et al., 2005), do not consider travel time and emphasize the assessment of spatial coverage, service frequency, vehicle capacity, and comfort of service. Polzin et al. (2002) proposed a "time-of-day" PTA evaluation, and discussed the fact that ignoring travel time could induce bias in PTA results. Gradually, PTA measures that consider travel time gained popularity. Among them, cumulative and gravity-based measures are the most widely used. The former gauges the number of opportunities reachable within a fixed cost threshold (e.g. travel time window) (Bhat et al., 2000; El-Geneidy et al., 2016; Geurs and Ritsema van Eck, 2001; Vickerman, 1974; Wachs and Kumagai, 1973). Thus, the selection of the threshold for cumulative measures greatly influences the accessibility results. The gravity-based accessibility measures count the number of opportunities reachable, normalized by a weighting cost function (Bhat et al., 2000, Bhat et al., 2006, Geurs and Ritsema van Eck, Hansen, 1959). It addresses the single-threshold limitation of the cumulative methods, yet its result is dependent on the weighting function specification. Our discussion of PTA will primarily be focused on these two measures for the rest of paper.

Prior to mid-2000s, the calculation of public transit travel time was challenging due to the unavailability or inconsistent format of transit schedule data. Simplified forms of public transit networks were used for calculating travel times (Beimborn et al., 2003; Kawabata and Shen, 2006; Kawabata, 2009; Polzin et al., 2002; Wu and Hine, 2003). Travel time was estimated based on service availability at a specific time-of-day, distance to and from transit stops, or a combination of both. Service frequency and reliability were used to measure the waiting time. In-vehicle travel time was estimated based on survey data or incomplete transit operation times. Yet, since travel time was estimated rather than measured with these approaches, there were estimation errors and losses of fidelity (Owen and Levinson, 2015). The recent advent in automatic data collection methods and uniformity of available data format has enabled and facilitated the measurement of travel time in public transit (Ma and Wang, 2014).

The creation of General Transit Feed Specification (GTFS) sparked a stream of research and applications on travel time dependent PTA. GTFS was developed in 2005 by Google and TriMet for transit agencies to publish their schedules, trips, routes, and stops data in an open-source format that is usable for Google Transit Web-based Trip Planner (Google, Inc., 2016). GTFS provides a detailed public transit schedule in plain text format that greatly facilitates travel time measurement. Most studies in PTA have focused on using GTFS data to measure travel times between origin-destination (O-D) pairs for specific times-of-day (Benenson et al., 2010; Krizek et al., 2009; Mavoa et al., 2012; Owen and Levinson, 2012). Yet ignoring the temporal fluctuation due to schedule variation leads to biased results (Farber and Fu, 2016). For example, stops that are served by bus routes operating only during peak periods might have an overestimated level of accessibility.

To address such limitations, Mavoa et al. (2012) jointly considered a PTA index and transit frequency measure. They argued that transit frequency measures represent the transit level of service. However, transit frequency is not necessarily constant throughout the day and the PTA index is measured based on specific time-of-day travel times. The value of the PTA index can vary significantly, depending on the specific departure time that the index is measured. For example, when measured at the moment where a bus is approaching the transit stop, the PTA index is close to its maximum value. Similarly, when measured at the time point when the bus has just departed from a stop, the value is approximate to its minimum. Thus, a single departure time method might lead to over- or underestimating PTA for different stops. Studies that use the minimum travel time throughout the day to measure PTA also suffer from similar issues of accessibility overestimation (Lei and Church, 2010; Owen and Levinson, 2012).

Fan et al. (2010) measured PTA for each hour-of-the-day, and averaged the values for analysis. Hourly measures can still be coarse in terms of resolution, as PTA can vary greatly from minute to minute (e.g., when bus arrives and waiting time is minimum versus when the bus leaves and waiting time is maximum). Fransen et al. (2015) and Owen and Levinson (2015) measured the PTA for each minute of specific peak periods of the day. They did not consider the service variability for other times-of-day in their calculation. Farber et al. (2016) addressed all the aforementioned issues by measuring travel times between all O-D pairs for each minute-of-the-day using GTFS. They developed a travel time ratio to represent its temporal fluctuation. The ratio was calculated based on the local average travel time (e.g. within 1 h of the selected trip) and global average travel time (all times-of-day). The proposed ratio is highly sensitive to the selection of time range (e.g., 1 h) for averaging the local PTA value. In addition, the value of the proposed ratio itself varies throughout the day. Thus, interpreting and analyzing the spatiotemporal fluctuation in PTA remains challenging.

Once the PTA is measured, analyzed, and interpreted, results help planners and transit agencies to identify areas in need of public transit service improvement. Yet as mentioned in the Section 1, poor PTA may be caused by geographical disadvantages rather than inadequate services. To the best of our knowledge, no study has successfully identified the underlying reason for poor PTA from the PTA analysis.

3. Study network and data preparation

UTA is the primary transit provider in the Wasatch Front Region of the State of Utah. UTA's services cover six counties, including Salt Lake, Utah, Davis, Weber, Box Elder, and Tooele. The transit network consists of 6265 transit stops for 125 transit routes encompassing bus, light rail, and commuter rail. Fig. 1 shows UTA's service network, including transit stops, Bus Rapid Transit (BRT), light rail (TRAX), and commuter rail (Frontrunner). In this study, we used UTA's network to implement the analytical framework. Transit stops were treated as transit service origins and destinations. The GTFS dataset for UTA's network is publicly accessible from the GTFS-data-exchange website (Google, 2016). It consists of six required and seven optional plain text files that have been formatted as Comma-Separated Values (CSV). The required CSV files include agency, stops, routes, trips, stop-times, and calendar, and provide detailed public transit schedules and associated geographic information. GTFS's stop file was used to extract the location of transit stops as the access points to transit services. The GTFS schedule data was used to measure the travel time between all O-D pairs at 10-min intervals.

Number of opportunities was represented using job density and salary/income at the destination stops/locations in the PTA analysis. This socioeconomic dataset was obtained from the Census Transportation Planning Product (CTPP) website (AASHTO, CTPP, 2016). The CTPP was developed based on a partnership between AASHTO and all states to provide census transportation data packages. These packages contain detailed information on demographic characteristics, home/work locations, and commuting trips. The number of jobs, number of workers, and salary/income at Traffic Analysis Zone (TAZ) level were extracted

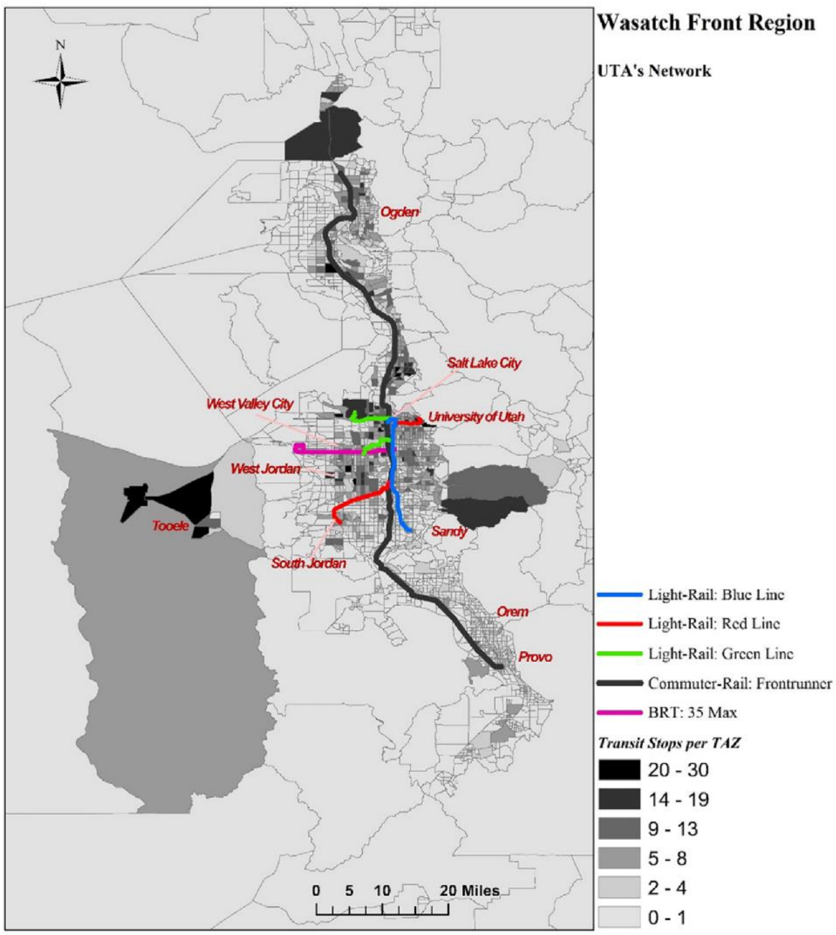

Fig. 1. Wasatch Front TAZs and UTA's transit stops.

from a CTPP-5-year-dataset from 2006 to 2010. The TAZ level provided the highest resolution of the required data compared to other geographic levels.

4. Methodology

This study aims to address the challenges in dynamic PTA analysis and transit gap causality. To that end, we used WATT as a PTA measure and elucidate the time interval selection to fully capture PTA in spatio-temporal dimensions. Average to Median WATT Ratio (AMWR) is developed as a unified ratio that captures the spatiotemporal variation of transit service provisions. The computational procedure for determining potential opportunities and travel time, considering both transit service quality and geographic location, is described in detail in this section. The methods for providing the fuller picture of dynamic PTA and transit gap causality are also presented. As a summary, Table 1 presents the details of all the indicators developed in our study.

4.1. WATT

WATT is a gravity-based accessibility measure, mostly used in large scale networks (Cao et al., 2013; Gutiérrez et al., 1996; Gutiérrez, 2001). It is also referred to as a location indicator (Gutiérrez et al., 1996). According to Fayyaz S. et al. (2017), WATT can be represented as:

$$WATT_{i,t} = \frac{\sum_{j=1}^{J} O_j * tt_{ij,t}}{\sum_{j=1}^{J} O_j}, j = 1, 2, \ldots, J, i \in J \tag{1}$$

where $WATT_{i,t}$ is the weighted average travel time of stop i at departure time t; O_j is the number of opportunities available at stop j; $tt_{ij,t}$ is the travel time from stop i to stop j at departure time t; and J is the total number of stops.

As mentioned in Section 2, the gravity-based accessibility measure's result is dependent on the weighting function specification. Gravity-based accessibility measure weighs opportunities based on a function of travel time (e.g. linear or nonlinear). On the other hand, WATT weighs travel time based on opportunities. Gravity-based accessibility measure is of opportunity nature and WATT is of travel time nature. Thus, super-linearity of distance-decay function will have no effect on WATT results.

In this study, WATT was measured for all transit stops within UTA's network at 10-min time intervals on a typical weekday (Tuesday) from 4 AM to 10 PM (transit in-service). 10-min intervals were chosen here as the desirable resolution since the minimum headway in the study network was 15 min. Such resolution ensured that every trip was considered during the travel time measurement. It is important to note that since WATT was measured every 10-min (e.g. 4:00 AM, 4:10 AM, 4:20 AM), the shift between the measuring moment and vehicle departure time (e.g. 4:00 AM, 4:15 AM, 4:30 AM) varies. This directly led to different waiting times throughout the day (e.g. 0, 5, and 10 min), which result in a full range of possible travel times, as well as PTA values.

4.1.1. Available opportunities

Potential opportunities at each TAZ was measured as:

$$O_{TAZ_i} = D_{TAZ_i} * I_{TAZ_i} \tag{2}$$

where O_{TAZ_i} is the potential opportunities available at TAZ_i; D_{TAZ_i} is the job density (number of jobs available divided by the area) of TAZ_i; and I_{TAZ_i} is the salary adjustment factor at TAZ_i. I_{TAZ_i} was calculated as:

$$I_{TAZ_i} = \frac{\sum_{k=1}^{K} WAS_{TAZ_k}}{K * WAS_{TAZ_i}} \tag{3}$$

where WAS_{TAZ_k} is the weighted average salary at TAZ_k; K is the total number of TAZs; and WAS_{TAZ_i} is the weighted average salary at TAZ_i. The weighted average salary at each TAZ was calculated by weighting the specific salary range with the number of jobs within that range. Eq. (3) shows that an increase (decrease) in weighted average salary of a TAZ will decrease (increase) the salary adjustment factor, and consequently decrease (increase) the potential opportunities available. I_{TAZ_i} effectively adjusts the attractiveness of the destination TAZs to the transit users. The relationship expressed between weighted average salary and potential opportunities by I_{TAZ_i}may at first seem counterintuitive. Note that high-salary job holders are less dependent on public transit since traveling by private vehicle is a feasible option. On the contrary, low-salary job holders are rather more dependent on public transit due to limited car ownership and the cost associated with it (Giuliano, 2005). By introducing I_{TAZ_i}, if a TAZ has a large number of high-paying jobs, then the attractiveness (a.k.a. potential opportunities) of that TAZ decreases for low-income transit users.

Potential opportunities available at each transit stop was then computed based on the potential opportunities of the TAZs intersecting within a 400-m buffer around the transit stop. The 400-m buffer was selected based on the distance that a transit user is willing to walk (Kittelson et al., 2003). One issue with this method is the possibility of duplicated inclusion of potential opportunities if transit stops are adjacent to each other such that buffer areas might intersect. To remedy this, an adjustment factor was used to prevent the duplicate assignment of potential opportunity (e.g. job density or jobs) to stops. The adjustment factor for each stop was calculated as:

$$AAF = \frac{A_0 + \frac{A_1}{2} + \frac{A_2}{3} + \frac{A_3}{4} + \ldots + \frac{A_n}{n+1}}{A} \tag{4}$$

where AAF is the adjustment factor for each stop, $A_0, A_1, \ldots, A_n$ are the shared area of stop buffer area with 0,1, ..., n other stops buffer area, and A is the buffer area of the stop ($A = \pi^* 400^2$). The potential opportunities available at stops was then adjusted as:

$$O'_{Stop_i} = O_{Stop_i} * AAF_{stop_i} \tag{5}$$

where O_{Stop_i} is the adjusted potential opportunities of *Stopi*, $OStop_i$ is the weighted average potential opportunities of *Stopi* calculated based on the intersecting area with different TAZs, and $AAFstop_i$ is the adjustment factor of *Stopi*.

Table 1
Summary of indicators developed.

Indicator	Description	Formula	Explanation	Resolution
WATT	Weighted Average Travel Time	$\frac{\sum_{j=1}^{J} O_j * tt_{ij,t}}{\sum_{j=1}^{J} O_j}$	Higher WATT = Lower PTA	Stop level, convertible to TAZ level
NPTS	Need for Public Transit Service	$WD_{TAZ_i} * NI_{TAZ_i}$	Higher NPTS = Higher dependency and demand for transit	TAZ level
PTAG	Public Transit Accessibility Gap	$WATT_{TAZ_i} * Norm(NPTS_{TAZ_i})$	Higher PTAG = Larger difference between demand and accessibility	TAZ level
AMWR	Average to Median WATT ratio	$\frac{\text{Average } WATT_{TAZ_i}}{\text{Median } WATT_{TAZ_i}}$	AMWR >1 = Lower temporal fluctuation in transit services	Stop level, convertible to TAZ level
NPTI	Need for Public Transit Improvement	$\frac{PTAG_{TAZ_i}}{(AMWR_{TAZ_i})^n}$	Higher NPTI = Higher PTAG caused by poor transit service	TAZ level

4.1.2. Public transit travel time

Public transit travel times between all stop-pairs were measured for each 10-min interval from 4 AM to 10 PM on a typical Tuesday using GTFS data. The total number of stop-pairs for the UTA network was 39,250,225 (6265 × 6265). Such a large network required extensive computation power for the PTA analysis (Farber and Fu, 2016; Farber et al., 2016; Owen and Levinson, 2015). To address this issue, an open source toolbox was developed in this study to compute travel times. The algorithm starts at each stop at a specific departure time and traces the next available trips serving this stop and other stops within walking distance. If the stops met on these trips are transfer stops (connected to new routes), then the next available trips serving the transfer stops are traced as well. This process continues until all the transit stops are met or the maximum allowable number of transfers are taken. Interested readers can refer to Fayyaz S. et al. (2017) for further details on the algorithm. The algorithm enables PTA analysts to customize the constraint on walking distance to/from origin/destination stops, walking distance between transfer stops, and the number of transfers. The WATTs computations for each specific departure time took approximately 1.5 h and the computation for all times-of-day took <6 days to complete on a normal desktop computer (Core™ i7-4790 3.6 GHz computer processor and 16 GB of RAM). The same process using Esri's ArcMap Network Analyst would take up to 165 days.

The measured travel time includes initial access time, waiting time, transfer access time, in-vehicle time, and destination time. Initial access time and destination time were computed on the basis of a 300-m walking time with a walking speed of 1.4 m per second (O'Sullivan and Morrall, 1996), assuming most jobs are located within a 200–400 m radius of a stop. The maximum number of transfers on each trip was set to three based on the fact that the majority of transit trips (over 90%) involve one or two transfers (Owen and Levinson, 2015). When a destination was not reachable within three transfers, the walking time between O-D was selected as the travel time. This prevented the WATT value from becoming extremely small or large considering the numerator in Eq. (1). Specifically, the impact of travel time to reachable destinations will be undermined if a large travel time value is selected for non-accessible destinations. The walking time is selected as travel time between an O-D in cases where transit travel time is longer than walking time and walking distance is <700 m.

$WATT_i$ for the time periods when no transit service was available was also calculated using the algorithm described above (i.e., treating all travel times as walking times). This $WATT_i$, similar to closeness centrality (Newman, 2001; Newman, 2004; Opsahl et al., 2010), indicates how close stop i is to all other stops in the transit network with distances weighted based on the number of opportunities available at destinations. When transit service is available, $WATT_i$ is still representative of a weighted closeness centrality since travel time to stops that are not accessible within three transfers is walking time. In our study, the difference between $WATT_{i,\ t}$ and $WATT_{i,\ 10:00\ PM}$ (when no service is available for most stops) reflects the quality of transit service. The closer the local maximum $WATT_i$ is to $WATT_{i,\ 10:00\ PM}$ (see Fig. 2), the worse the transit service is at the stop i. This directly impacts the average and median WATTs and such effect is captured in the AMWR.

Although the aforementioned PTA analysis was carried out at a stop level, when trying to identify the transit service gap, the analysis needed to be mapped to the TAZ level to be comparable with NPTS in that TAZ. Thus, once the WATT was measured for each stop, the average WATT of stops within each TAZ was used as the surrogate for the TAZ's WATT for transit service gap identification.

4.1.3. Temporal fluctuation of transit service and AMWR

The AMWR was used to demonstrate temporal fluctuation of service. Each stop's AMWR was determined as the ratio between its average WATT and median WATT throughout the day. As shown in Fig. 2(c)

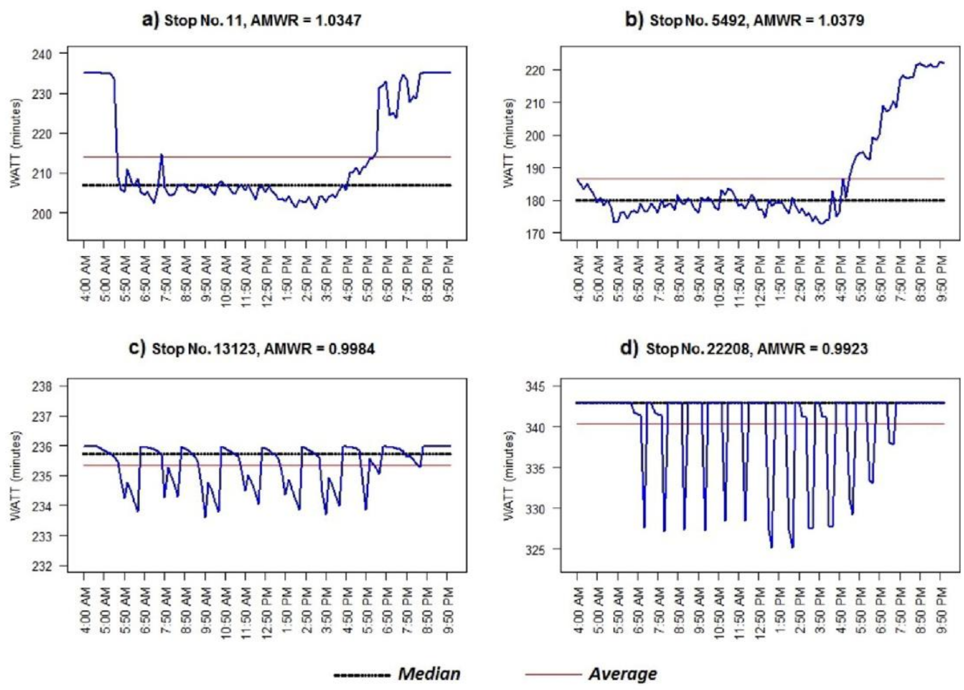

Fig. 2. Temporal fluctuation, average, and median value of WATT throughout the day for a) stop No. 11, b) stop No. 5492, c) stop No. 13123, and d) stop No. 22208.

Table 2
Comparing different measures used to quantify temporal variability of PTA.

Stop no.	AMWR	Standard deviation	Coefficient of variation	W (Fourier's fundamental frequency)	Transit frequency
11	1.0348	12.59	0.06	0.31	10.40
5492	1.0379	15.05	0.08	0.05	25.00
13123	0.9985	0.71	0.00	0.52	0.50
22208	0.9923	5.46	0.02	1.04	1.00

and (d), when AMWR < 1 (i.e., WATT distribution negatively skewed), temporal fluctuation in service was large (compared against the WATT range). A majority of the WATTs during the day were closer to the maximum. On the other hand, in Fig. 2(a) and (b), when AMWR > 1 (i.e., WATT distribution positively skewed), the temporal fluctuation in service was small (compared against the WATT range). In the latter case, the transit service appeared to be frequent and consistent.

High variation of PTA leads to unexpected delays and reduce the quality of service. In order to determine the quality of transit services at each stop, the probability of WATT for each random departure being closer to minimum (or local minimum) WATT is compared to maximum (or local maximum) WATT. In other words, for a random departure time, if the expected WATT is closer to the minimum WATT than maximum WATT, then the quality of service is better. It is noted that, by comparing WATT graphs across these four stations, Stop No. 5492 has the best transit service, followed by Stops No. 11, No. 13123, and No. 22208. Table 2 shows the comparison of AMWRs, Standard Deviations, Frequency, Coefficients of Variation, and Fourier Transform Frequency (w) for these four stops on quantifying the temporal variation of accessibility (WATT).

Standard deviation cannot logically distinguish level of service as shown in Table 2 (i.e. No. 13123 has the smallest standard deviation). The Coefficient of Variation can discern the service quality when the standard deviation of WATT is relatively large, yet fails when standard deviation of WATT for that station is small since it is very sensitive to standard deviation values. The Fourier's fundamental frequency value was calculated from fitting the following specification to WATT graph throughout the day:

$$F(t) = \beta_0 + \sum_{i=1}^{8} \beta_i * \cos(w * t) + \alpha_i * \sin(w * t) \tag{6}$$

where $\beta_0, \beta_i, \alpha_i$, *and* w are parameters that must be estimated and t is the time interval counter. Lower values of W indicate better transit service. Although it provides correct ranking for these four stops, the values do not scale. For example, the quality of service for Stop No. 5492 is

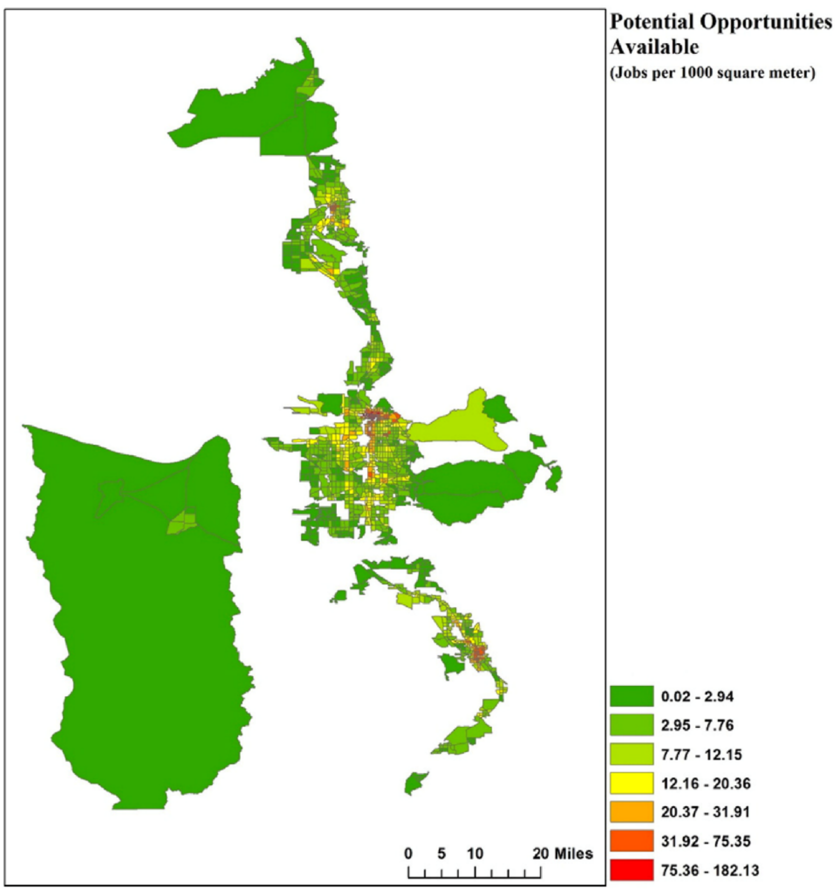

Fig. 3. Potential opportunities available at each TAZ served by public transit.

estimated six times better than Stop No. 11 which is apparently incorrect. Finally, the frequency measure neither produces correct ranking nor scales properly. Based on the frequency measure, service provided in Stop No. 5492 is 2.5 times better than Stop No. 11, which appears not to be aligned with the WATT patterns shown in Fig. 2, where only marginal differences between the two are detected in early morning and late afternoon hours. This is due to the fact that frequency measure does not consider the waiting time for transfers (coordination between routes), connected stop headway, and headway fluctuations throughout the day.

4.2. Public transit service gap

In order to detect public transit service gaps in the analysis network, public transport needs (NPTS) and provisions (WATT) must be compared. NPTS in this study was measured using number of workers and average income at each TAZ:

$$NPTS_{TAZ_i} = WD_{TAZ_i} * NI_{TAZ_i} \tag{7}$$

where $NPTS_{TAZ_i}$ is the NPTS at TAZ_i; WD_{TAZ_i} is the number of workers living in TAZ_i divided by the area of TAZ_i; and NI_{TAZ_i} is the income adjustment factor at TAZ_i. NI_{TAZ_i} was calculated as:

$$NI_{TAZ_i} = \frac{\sum_{k=1}^{K} WAI_{TAZ_k}}{K * WAI_{TAZ_i}} \tag{8}$$

where WAI_{TAZ_k} is the weighted average income at TAZ_k; K is the total number of TAZs; and WAI_{TAZ_i} is the weighted average income at TAZ_i.

To find areas with high NPTS and poor PTA, an indicator named Public Transit Accessibility Gap (PTAG) was defined as:

$$PTAG_{TAZ_i} = WATT_{TAZ_i} * Norm(NPTS_{TAZ_i}) \tag{9}$$

where $PTAG_{TAZ_i}$ is the PTAG for TAZ_i; $WATT_{TAZ_i}$ is the average WATT of stops in TAZ_i; and $Norm(NPTS_{TAZ_i})$ is the normalized (in the range of 0 to 1) value of NPTS for TAZ_i. The NPTS is normalized to make the indice commensurable in Eq. (9). The resulting PTAG allowed comparison between different TAZs to identify areas that need attention. A high PTAG value indicates poor PTA and high NPTS.

Finally, the AMWR was used to determine the underlying reason for high PTAG – poor transit service or geographical disadvantage. The Need for Public Transit Improvement (NPTI) was developed by

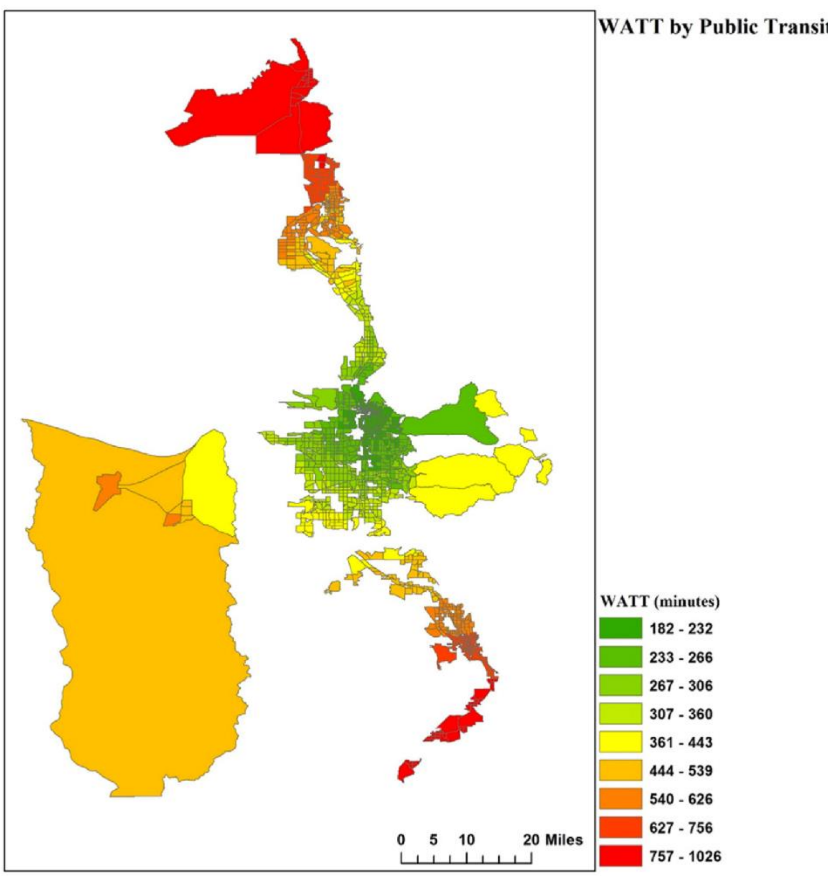

Fig. 4. WATT for each TAZ served by public transits (minutes).

combining PTAG and AMWR as follows:

$$NPTI_{TAZ_i} = PTAG_{TAZ_i} / \left(AMWR_{TAZ_i}\right)^n \tag{10}$$

where $NPTI_{TAZ_i}$ is the NPTI for TAZ_i; $PTAG_{TAZ_i}$ is the PTAG of TAZ_i; $AMWR_{TAZ_i}$ is the average AMWR of stops in TAZ_i; and n is the scaling parameter. Note that WATT and AMWR in Eqs. (9) and (10) were geographically standardized (converted from stop level to TAZ level) for joint usage. In UTA's network, AMWR is in the range of 0.090 to 1.107. Yet small changes (e.g., 0.01 in magnitude) in AMWR can result in significant variations in quality of service (Fig. 2). The current form of AMWR is unable to effectively express the NPTI pattern since its range is relatively small (around 1). Thus AMWR needs to be scaled or normalized. As mentioned in the paper, AMWR >1 indicates relatively good transit service and vice versa. Normalization methods such as feature scaling are based on the position of value on its distribution with augmented or shrunken range. Normalization methods cannot provide sufficiently large (or small) values for AMWR to enable the shift in NPTI distribution as described above. Such issue can be remedied by power scaling. Power scaling will penalize the AMWR <1, and reward the AMWR >1. The scaling parameter is selected in a way to enable the shift with the following formula:

$$\frac{Mean_{PTAG} + St.Dev._{PTAG}}{Mean_{PTAG} - St.Dev._{PTAG}} = \frac{Mean_{AMWR^n} + St.Dev._{AMWR^n}}{Mean_{AMWR^n} - St.Dev._{AMWR^n}} \tag{11}$$

where $Mean_{PTAG}$ and $Mean_{AMWR^n}$ represent average values in PTAG and scaled AMWR distributions, respectively, and $St.Dev._{PTAG}$ and $St.Dev._{AMWR^n}$ represents the standard deviation values in PTAG and scaled AMWR distributions, respectively. This formula will ensure that scaled

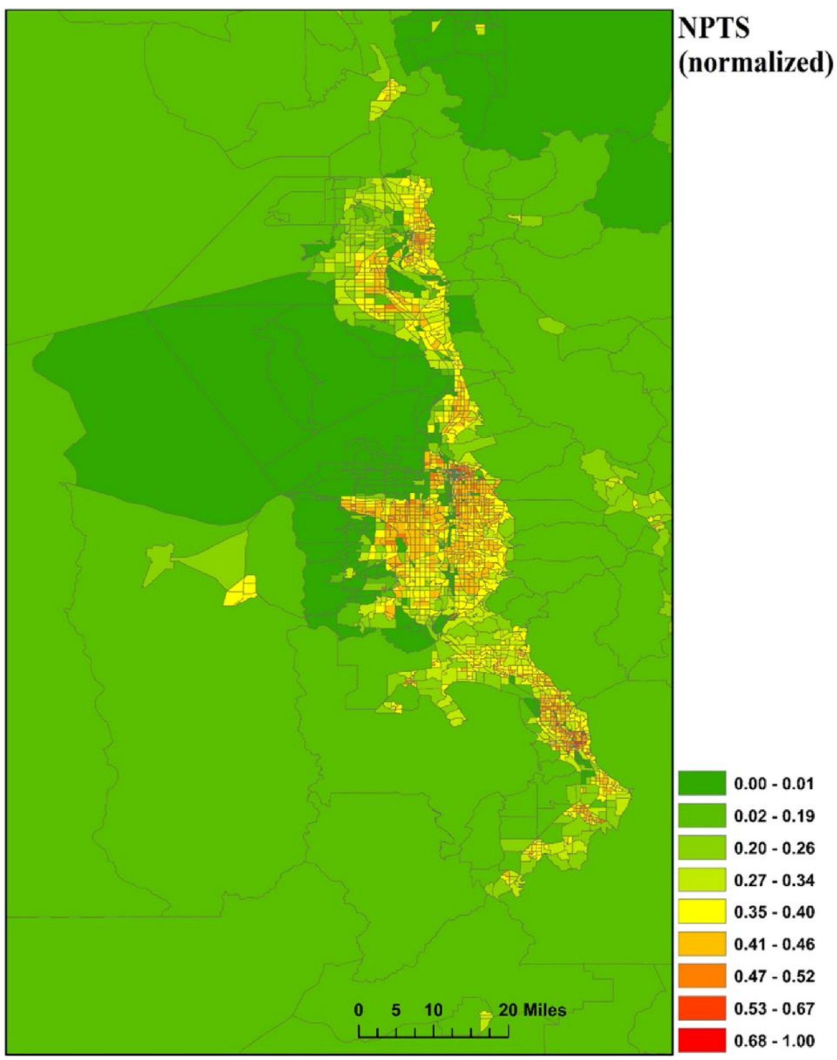

Fig. 5. NPTS for each TAZ.

AMWR can move a TAZ over almost all NPTI distribution. Note that, range of [Mean − St.Dev., Mean + St.Dev.] covers almost 80% of TAZs in both PTAG and scaled AMWR distribution.

Higher values of NPTI is thus associated with poor PTA, high NPTS, and poor available transit service. High NPTI values indicate the need for transit service improvements. Planners and public transit agencies can use this indicator to prioritize future projects and investments.

5. Results and discussion

The indicators developed in the Methodology section were implemented using UTA's transit network. The value classes for all maps (i.e. Figs. 3–8) in this section are determined using Jenks Natural Breaks algorithm (De Smith et al., 2007). The boundaries are set to minimize the within class variance and maximize between class variance. As a result, this data classification method is used to show the differences across TAZs in terms of values, scales, and clusters.

Fig. 3 shows the potential opportunities available at each TAZ. Note that potential opportunities were measured based on job density weighted by the salary range at each TAZ. The majority of potential opportunities are concentrated in the downtown Salt Lake City area. The number decreases gradually moving towards the west (West Valley City). The University of Utah, Provo, Orem, and Ogden also have relatively high concentrations of opportunities. West Jordan, South Jordan, and Tooele have relatively low concentrations of opportunities. Generally, the number of available opportunities are higher in urban areas

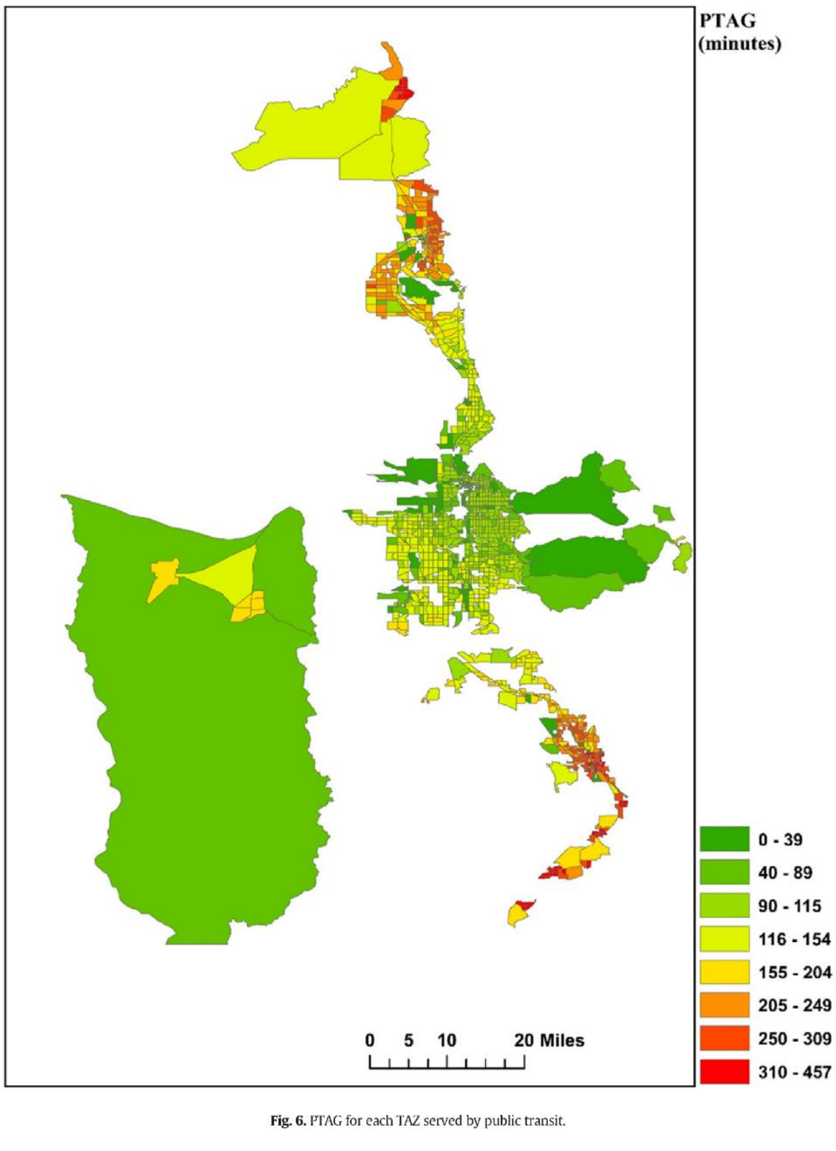

Fig. 6. PTAG for each TAZ served by public transit.

compared to rural areas. Fig. 3 indicates everything else being equal (i.e., same transit service at all TAZs), areas that are further away from the high number of potential opportunities have lower PTA.

The measured WATT of TAZs are shown in Fig. 4. Essentially, poor PTA is associated with high WATT. Fig. 4 shows that downtown Salt Lake City has good PTA and it is trending downward as one moves towards the city outskirts. In other words, people living closer to downtown Salt Lake City can access more jobs within shorter periods of time than people living in other areas such as West Valley City. This is consistent with the findings presented in previous studies (Owen and Levinson, 2015) and demonstrates the importance of geographical location on PTA.

NPTS was then computed and shown in Fig. 5. Note that high NPTS appears in Salt Lake City, West Valley City, south Downtown Salt Lake City (towards Sandy), Tooele, Ogden, and Provo. Even though NPTS is widely dispersed over the region, UTA's service covers all the TAZs with high demand (NPTS >4.56) with several stops per TAZ, indicating good public transit service coverage.

The NPTS and WATT were further combined to measure PTAG. TAZs with relatively high PTAG denote areas that have high demand (dependency) for transit services and poor PTA. As shown in Fig. 6, Provo, Orem, Ogden, and Tooele experience the highest PTAG and consequently highest gap between NPTS and PTA. High PTAG in rural (less urbanized) areas was expected due to the remote access to high potential opportunities in these locations, yet some rather more urbanized areas, such as South Jordan, also demonstrated high PTAG.

It is important to reiterate that AMWR reflects the temporal variability of transit service. As shown in Fig. 7, areas on the edge of the network usually experience larger temporal fluctuation of PTA. This is due to the fact that inner TAZs are usually served by several transit routes resulting in more frequent service, while outskirts experience limited transit service (e.g., one route). Consequently, a single route at these outskirt locations could serve as the only option for accessing different locations within the network and frequency of access is confined to the frequency of that route (e.g., Fig. 2 (d)).

Finally, NPTI was calculated using Eq. (5) to distinguish TAZs with poor public transit service and high PTAG. Fig. 8 shows that Tooele is among the top priorities for public transit service improvements. Tooele is a small city located on the western side of the Oquirrh Mountains. Because of its close proximity to Salt Lake City, many Tooele residents

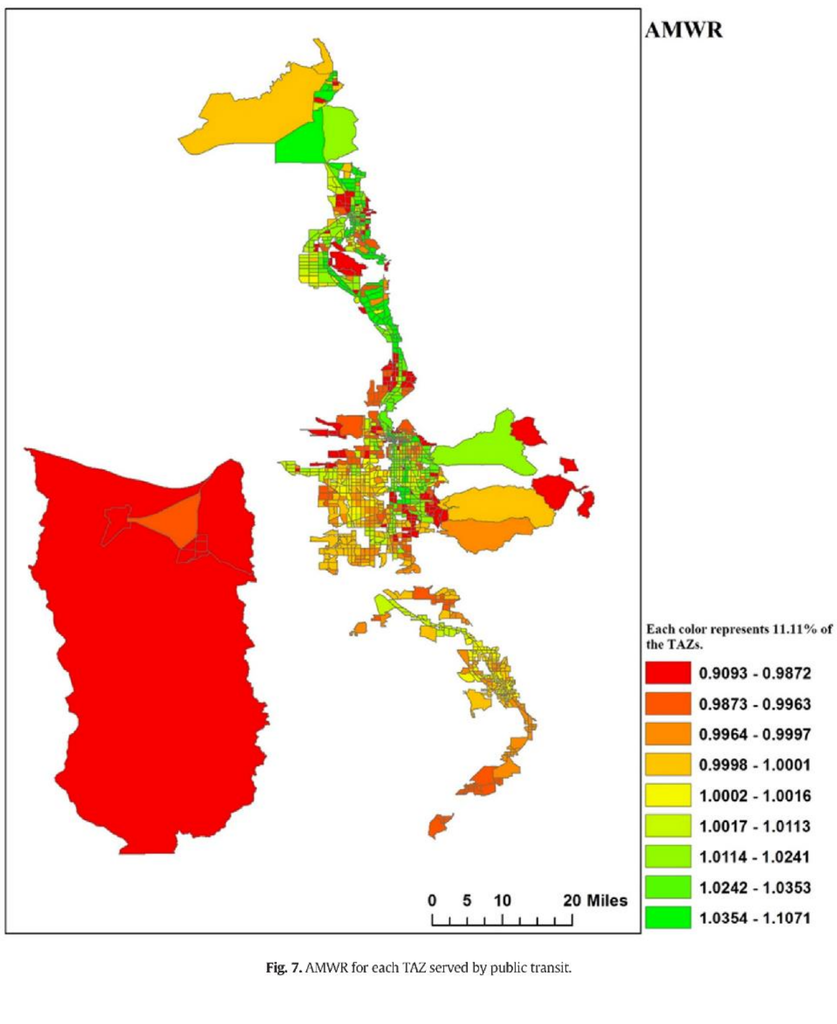

Fig. 7. AMWR for each TAZ served by public transit.

regularly commute to Salt Lake City for work. The UTA network serves Tooele with only four bus routes for limited hours during the day. As a result, the area has high demand (dependency) for transit, yet relatively poor PTA, and more importantly, high temporal fluctuation of PTA, which makes it have the highest needs for public transit improvements.

Several areas in Ogden also demonstrate high NPTI. Even with the operation of commuter rail in Ogden, these areas still appear to have high NPTI. The TAZs in and around Ogden are connected to commuter rail by one or two transfers, and the transfer buses are operating at a minimum headway of 30 min. This increases the temporal variability of access to commuter rail and consequently decreases the AMWR. As a result, these TAZs become high priorities for improvement. There are several TAZs in south and east Murray that require attention as well. The high NPTI value at these locations are mainly caused by limited numbers of routes operating at large headways.

The NPTI results show that UTA is providing a reasonably good service in West Valley City. This is partly because of the operation of a BRT line in the area since 2008, providing efficient access to light rail stops. This can be observed in Fig. 4, where the green area extended more widely to the west side of Salt Lake City when compared to the east side. Fig. 7 shows that AMWR is higher in TAZs where BRT operates than the neighboring TAZs. Moreover, commuter rail has stretched the green area to the south and north sides of Salt Lake City. Fig. 7 also indicates that, along the commuter rail route, the temporal fluctuation in PTA is lower than in neighboring TAZs. This is partly due to the relatively faster access to desired locations provided by the frequent service of

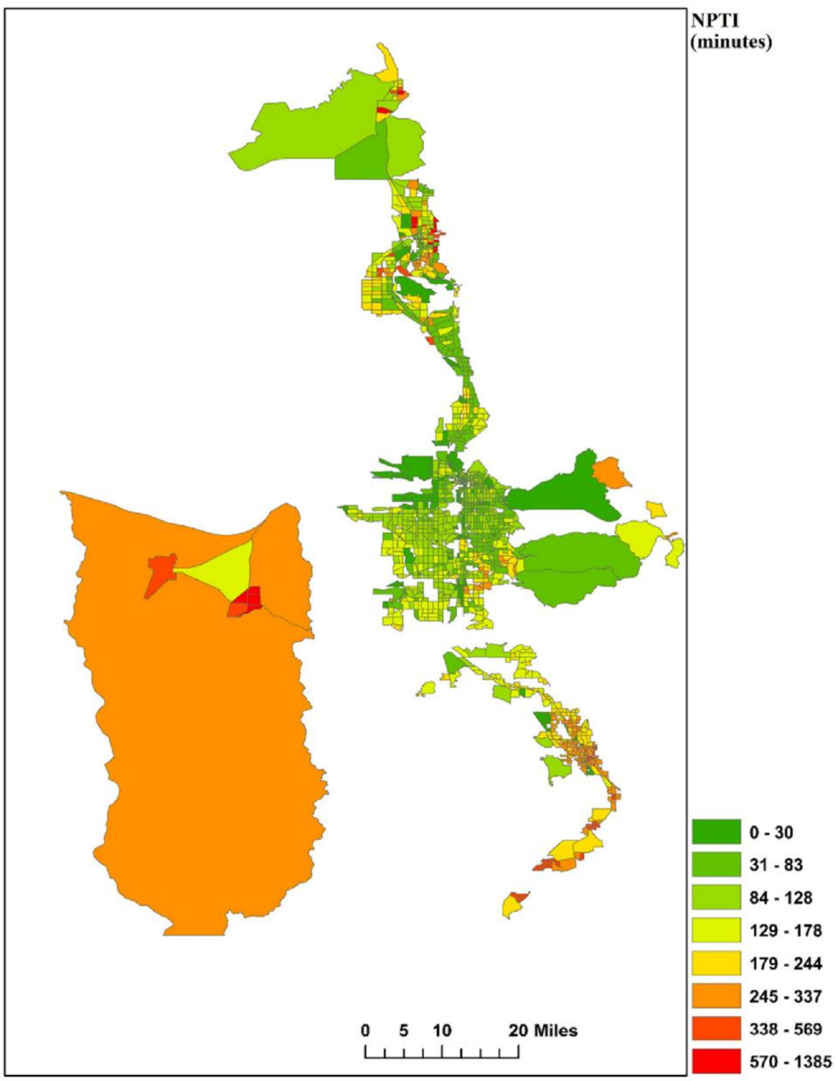

Fig. 8. NPTI for each TAZ served by public transit.

commuter rail. The same trend can be observed for TAZs served by light-rail routes. This shows the positive impact of fast public transit routes on accessibility. However, the high NPTI of some neighboring TAZs shows the importance of feeder routes. Specifically, feeder routes operating on long headways in high demand areas will significantly compromise the benefits of fast public transit services (e.g. BRT, light rail, commuter rail).

The importance of geographical location on PTA can be better observed by comparing Figs. 6 and 8. For example, Provo and Orem are experiencing relatively high PTAG, yet moderate NPTI, indicating good transit service provisions already. As a result, the gaps (i.e., poor PTA and high NPTS) is mainly due to the relatively long distances between these areas and Salt Lake City (where most opportunities are located). In such cases, improving transit service (e.g. frequent and larger coverage) will only provide marginal benefits to the area and might not be a cost effective investment.

The temporal fluctuation of PTA can be further analyzed at a stop level (Fig. 2) to investigate possible flaws (e.g. incoordination) in existing services. For example, Fig. 2(d) is a stop served by only one feeder route that works on a one-hour headway. The local minimums for the WATTs represent the time when the bus is approaching the stop. The differences between the peaks (local minimums) is mainly due to the wait time at the stop (counted as first transfer). The larger the time gap between peaks, the less synchronization there is between the feeder bus and fast transit service. In the case of Fig. 2(d), no significant incoordination is observed.

The average WATT within the entire UTA network across the day is shown in Fig. 9. Note that lower WATT (higher PTA) is observed between 5:30 to 7:30 AM, which corresponds to lower headways during morning peaks towards the denser job areas. The same lower trends occur from 3:30 PM to 5:30 PM where more frequent services are offered in the opposite direction of the morning commute. These results indicate that the current transit services meet the need of daily commute patterns. However, for people who work on night shifts, commuting by public transit becomes much less convenient.

6. Conclusions

Several PTA measures have been developed over the past several decades. Yet the usage of travel time in PTA measures has only emerged with the introduction of GTFS. Dynamic PTA, considering the spatiotemporal dimensions in accessibility variation, has gained popularity as a result. Yet, analyzing the temporal fluctuation of PTA remains challenging due to the computational inefficiency and added temporal dimensions. Additionally, inadequate public transit service has generally been assumed to be the cause of poor PTA, without fully considering the potential geographical disadvantage of areas-in-study.

In this paper, we showed that a dynamic PTA analysis can be implemented in an efficient manner using a computationally elegant algorithm. The algorithm enables the measurement of travel time at multiple departure times throughout the day. The time resolution was selected in such a way to reflect all possible waiting times and schedule variations. WATT was adopted in this study as a gravity-based PTA measure. Using UTA's transit network as a case study, the results indicated that PTA is generally higher in downtown Salt Lake City and trends downward as the areas extend to city outskirts. This is consistent with findings in previous studies and shows the importance of geographical location in PTA. AMWR was developed to capture the quality of transit service and its temporal fluctuation throughout the day. A higher AMWR (>1) implies relatively consistent transit service and constant WATT. A lower AMWR (<1), on the other hand, indicates high variability in transit service and PTA. The results show that AMWR is generally lower in TAZs that are located at the edge of network due to the limited feeder routes connecting them to the inner loop. A series of indicators that are intuitive to interpret were developed to identify the varying causes of poor PTA and areas with immediate needs for transit service improvements. NPTS was measured based on employment density and income in each TAZ. NPTS and WATT were then jointly used to identify the gaps in the existing services (PTAG). NPTI was developed to uncover the convoluted causes of poor PTA.

The analysis on UTA's network shows the positive impact of fast transit services such as commuter rail, BRT, and light rail, on improving the transit accessibility. The spatial inconvenience can also significantly jeopardize PTA of the study area. As an example, Provo and Orem, cities located approximately 45 miles away from downtown Salt Lake City, have large transit accessibility gaps (high PTAG), yet good transit service is provided within the area. Further improving transit service (e.g. frequent and larger coverage) will only provide marginal benefits to the area and might not be a cost effective investment.

The PTA analysis, as demonstrated in the paper, can be conducted at high resolution (stop level) as well. As shown in Fig. 2(d), a feeder stop WATT can help identify the incoordination between the feeder route and the connected faster transit service. The proposed method is solely based on publically available datasets, including GTFS and CTPP. The analytical framework presented is reproducible for any public transport network and can help unveil the causes of inefficient PTA and areas in need of service investment. Based on the above discussion, two intriguing topics emerge. First, as a follow-up research on the result, it is

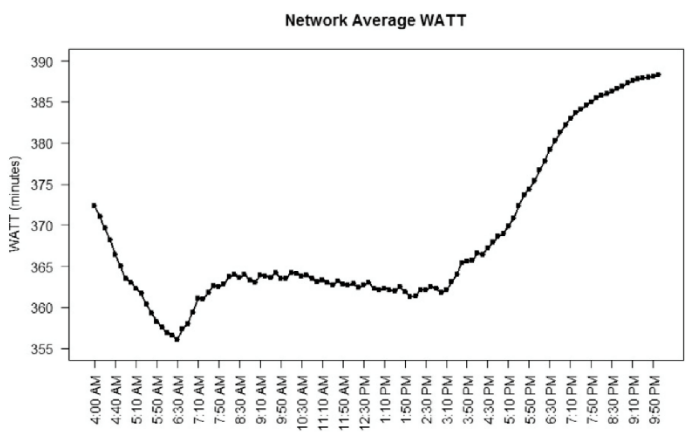

Fig. 9. Average WATT of all stops in UTA's network.

necessary to incorporate salary profile of transit users to further refine the potential opportunity measurement and NPTS, providing more insights on how PTA affects different transit users. Second, it might be interesting to perform pattern matching by categorizing transit stops based on their PTA to identify the mismatch between existing services and transit agencies' expectation.

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CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

Recent advancements in sensing technologies and data management along with the open-data movement provide a large and detailed source of information that was not easily accessibility (if accessible at all) before. Researchers and decision makers soon started to take advantage of such data sources by developing mathematical and statistical modeling techniques to back up policies and guide future plans. Public transit authorities were not an exception in employing new sensors, data management, and new analysis methods to guide decisions related to service investments, land use development, and operation policies. The main goal of this research was to develop data-driven analysis that utilizes newly available datasets and provides results to guide decision-making processes in public transit. The first step in developing such data-driven methods is to address the challenges associated with the data. This dissertation tries to address three of those challenges as follows:

1) How to incorporate and analyze missing data due to lack of electronic footage.
2) How to perform high-resolution performance measurements that require extensive computation.
3) And how to interpret the high-resolution results.

To address each challenge, a study was designed. The first challenge was explored in a quest to find missing data on the fare payment methods without electronic footage, and their impact (among other factors) on bus Dwell Time (DT). For this purpose, statistical modeling and optimization techniques were jointly used to develop a methodological framework based on Automatic Passenger Count (APC), Automatic Fare Count (AFC), and Automatic Vehicle Location (AVL) datasets. The Bus Rapid Transit (BRT) route 35 MAX in Utah Transit Authority's (UTA's) network was selected to showcase the aptitude of the method in estimating the missing data including cash payers and prepaid pass holders. The second challenge was attacked by designing a new dynamic all-pair shortest path algorithm based on the public transit characteristics. The developed algorithm significantly reduces the amount of required computation to the point that enables the calculation of dynamic Public Transit Accessibility (PTA) on a normal desktop computer. The developed algorithm was implemented in a toolbox working solely based on publicly-available datasets including Google Transit Feed Specification (GTFS) and census data. The algorithm and toolbox were tested and their superiority over other available software and algorithms was proved by experimental evidence. Challenge three came into existence due to the added temporal dimension of the PTA results. The third study explored various methods in interpreting the dynamic PTA. Innovative indices were developed and implemented on UTA's transit network to capture the temporal fluctuation of PTA throughout a day. The proposed method resulted in effective interpretation of dynamic PTA, transit gap, and associated causes of transit gap. This dissertation manifested that utilizing newly available datasets not only improves the resolution and accuracy of transit performance measures, but also takes a step further to enable studying factors (e.g., station placement impact on DT) impacting such measures and quantifying critical indices (e.g., transit gap causality analysis and developing NPTI) for investment decision making that were not possible before. This chapter discusses the contributions of each study (presented in Chapter 2, 3, and 4) to the relevant body of literature, followed by the summary of the research limitations. Finally, recommendation for future studies are mentioned.

5.1 Research Contribution

5.1.1 Fare payment structure and dwell time modeling. The main contribution of this study is developing a method to estimate the number of passengers using nonelectronic fare payment methods (that don't have electronic footage) and their impact on DT. Route 35 MAX BRT was selected to showcase the proposed analytical framework. The number of passengers boarding using cash payment (B-Cash) and prepaid pass payment (B-TVM) were estimated for each observation and incorporated in the statistical model. The disaggregated model showed an excellent goodness of fit with R^2-value of 0.90, while the aggregated model had R^2-value of 0.59. The difference in R^2-values of the disaggregated and aggregated model shows that the boarding time of various nonelectronic fare payment users are significantly different from each other. Thus, aggregating and averaging the impact of different nonelectronic fare payment methods on DT result in an unreliable and inaccurate model. No previous study has estimated the disaggregated impact of nonelectronic fare payment methods using the automatically collected data.

The consensus of DT modeling distinguishes between sequential (where passenger activities occur subsequently) and simultaneous (where passenger activity occur simultaneously) boarding and alighting. Simultaneous DT model requires categorization of observations based on the passenger activity (i.e., boarding, alighting, and atypical activity) that controls DT. Past studies based on APC, AFC, and AVL datasets were forced to use sequential models due to unavailability of behavior-controlled categorization method, which severely impact the accuracy of the results. The second contribution of this study is the introduction of a new method to categorize behavior-controlled DT observations, which allows for the use of a simultaneous DT model on automatically collected data. The method has been applied to route 35 MAX BRT. The behavior-controlled models showed significant improvement on both R^2-value and variables' confidence interval.

The noise filtration process in automatically collected data (i.e., APC, AFC, and AVL) has been poorly documented in previous studies, and oftentimes is limited to a simple filtering threshold. The third contribution of this study is identifying and documenting various noise sources caused by device malfunctions, mismatches between APC and AFC datasets, and passenger atypical activities. The noise management process documented in this research not only eases the future implementation of the method, but also shows the importance of noise management in any study based on APC, AFC, and AVL datasets. For example, the main goal of the APC device is to monitor the ridership and passenger flow in transit routes. This is by aggregating the number of passengers boarding/alighting over a specific time period or station. Identifying noises is challenging (if possible) after aggregation. These noises can significantly influence results. Thus, an observation-level noise screening, such as the one provided in this study, is required to ensure the results' reliability and accuracy.

The influence of different fare payment methods on DT may vary across transit routes. It is desirable to measure such influence uniquely for each transit route, instead of generalizing the results of one route to others. A good solution thus offers an inexpensive method that can be applied to any transit route or system. Past studies were based on manually collected data, which is time-extensive, cost-expensive, and suffers from limited sample size. For example, manually collecting the data used in this research requires about 65 persons working 160 hours for a month. The fourth contribution of this research is proposing a methodology that is inexpensively transferable to any transit route or system that is equipped with APC, AFC, and AVL devices. For example, applying the proposed method to a new route will take less than a day for one person.

The proposed methodology is valuable in guiding the practitioners and researchers for evaluating the impact of not only fare payment methods, but also dead time, stop placement, stop design, and built environment on DT and bus operation. Even though the crowding effect, time of day, and day of week were explored and yielded statistical insignificance in the DT model for 35 MAX BRT, the method provides the required platform for incorporating those variables in the model. In addition, estimating the number of passengers using nonelectronic fare payment methods allows for further operational analysis such as estimating the number of fare evaders, Ticket Vending Machine (TVM) cost–benefit analysis, and instructional guidance to facilitate a smooth boarding and alighting process, all of which are an effort to improve transit efficiency and reduce DT variation.

5.1.2 Algorithm for dynamic transit accessibility analysis. Time-dependent all-pair shortest path, as part of dynamic PTA measurement process, is computationally expensive and time consuming using the readily available software. As a result, past studies have either measured PTA for limited time-of-day (low-resolution) or used super-machines for such computations. This study introduces an innovative algorithm carved to take advantage of public transit network characteristics and reduce the high-resolution dynamic PTA computations. The main contribution of the study is enabling normal desktop computers to perform such computation. The algorithm has been compared to its peer algorithm and commercial software. The experimental evidence showed significant reduction on computational time.

Past studies have ignored the feasibility of transit trips, when measuring the shortest path. This leads to overestimation of PTA. It has been well-established that feasibility of a transit trip is directly impacted by number of transfers and walking distance. Our proposed algorithm not only limits the number of transfers and walking distance allowed for a transit trip, but also takes advantage of these characteristics to improve the time complexity of the algorithm. As a result, the proposed method calculates PTA more realistically in much shorter time compared to the past studies.

The PTA analysis was dependent on the access to data sources, commercial software, implementation techniques, and computing power. The proposed method and developed toolbox eliminate such dependencies and thus allow for easy implementation and transferability. This study is solely based on publicly available datasets including GTFS and census data. The proposed algorithm has been implemented in an open-source toolbox. The toolbox replaces commercial software for PTA analysis and doesn’t require super computation power. In addition, the toolbox can be easily modified for different purposes such as identifying service coordination. The source code for the toolbox will be available on GitHub once the study is published.

The number of transfers allowed has shown significant impact on the total calculation time of all-pair shortest path of the network. For example, preliminary analysis showed that limiting number of transfers to three (five) will significantly reduce (increase) calculation time. In addition, limiting number of transfers to three showed reduced resolution of results, whereas limiting number of transfers to five doesn't generate significant bias from limiting number of transfers to four. As a result, this study shows that limiting the number of transfers to four not only provides high-resolution results considering the feasibility of transit trip, but also has reasonable computation time.

Finally, this study offers valuable insights for interpreting dynamic PTA by analyzing the impact of a transit route's headway, transit route's operation speed, station's geographic location, and service coordination on PTA fluctuation throughout the day. The station-level WATT graph is a powerful tool for public transit agencies and planners in conducting microscopic transit performance analysis. It not only captures the impact of transit operation features such as headway, operating speed, coordination, and travel time, but also associates them with land use and potential opportunities available (geographic distribution of attractiveness).

<u>5.1.3 Public transit accessibility and transit gap causality analysis.</u> Limited number of studies had measured dynamic PTA to date, but there exists no general consensus on the interpretation of it. This study explores different statistical methods (e.g., coefficient of variation, Fourier's fundamental frequency, standard deviation, and transit frequency) to interpret the temporal fluctuation of PTA. This research introduces a unified ratio that captures the spatiotemporal variability of transit services throughout the day. The ratio is robust to parameter or scale selection. This allows the conversion of time-series of PTA values into a single ratio, which eases the interpretation of dynamic PTA.

In past studies, the concept of public transit accessibility gap or mismatch had been formulated as subtraction of normalized (by feature scaling method) values of need for transit service and PTA. As a result, the measured transit gap was suffering from loss of scale, loss of geographic and quality of service effect, and dependency on outliers. A new formula is proposed for measuring transit gap that replaces the subtraction with multiplication to overcome those challenges. As a result, the measured transit gap allows for transit mismatch (gap) causality analysis.

Poor PTA due to inadequate transit services can be remedied by a transit agency via transit investments. However, a remote area with good transit services may still experience poor PTA. There is not much a transit agency can do in this latter case other than play one part of much broader land development efforts. In other words, the spatial inconvenience can significantly jeopardize PTA of the study area. As an example, the results of the method showed that Provo and Orem cities, experiencing large transit accessibility gaps (high PTAG), are provided by good transit service. Further improving transit service (e.g., more frequent service and larger coverage) will only provide marginal benefits to the area and might not be a cost-effective investment. There is therefore a critical need for PTA analysis to reflect and distinguish between both causes of transit gap to avoid making poor investments in the wrong sets of solutions. This research introduces the concept of transit gap causality analysis for the first time and developed a ratio to measure the need for transit improvements (investments). This allows for discerning the impact of quality of transit service and geographic location on transit gap.

One of the major contributions of our study is developing a scaling measure that fits the geographical characteristics of the study area. Gravity accessibility is a relative measure in nature, meaning that the size of study area will affect its value. For example, in a very large network (e.g., entire USA), PTA to jobs for all TAZs in Wasatch Front Region (WFR) will be almost the same, because of the wide dispersion of jobs across the country. In order to accurately analyze such relativity, the scaling parameters must be adjusted accordingly. In particular, the scaling factor of Average to Median WATT Ratio (AMWR) should be selected based on the distribution of Public Transit Accessibility Gap (PTAG) values to capture the network size impact. It is important to mention that if the study network size becomes smaller, then WATT values become smaller and the AMWR values become larger. In that case, the scaling factor for AMWR is closer to one. On the other hand, when the study network size grows, the WATT values become larger and the AMWR values become smaller. In that case, the scaling parameter tends to be larger. Other measures such as transit frequency (which is commonly used in previous studies) will remain constant regardless of the change of network size and are unable to adjust with such changes, which will bias the results.

The time resolution for measuring PTA has significant impact on accuracy of results and computation time. As time resolution increases, the required computation time and the accuracy of results increase. This research provides guidance on selecting the maximum required time interval based on the minimum headway in a studied transit network for measuring PTA that reflects all possible waiting times and schedule variations. The time interval selection method proposed will significantly reduce computation time, while it has limited impact on accuracy of results.

Finally, the results of the method implementation on UTA’s network show the impact of service coordination and fast transit services on PTA and transit gap. In particular, poor coordination between feeder routes and fast transit services severely reduces the PTA of studied region. Such miscoordination is inexpensively fixable by modifying the feeder's route schedule. The fast transit services such as bus rapid transit, light rail transit, and commuter rail have significantly improved the PTA of the regions with immediate access. It is important to mention that such insights are only revealed when the impact of geographic location of studied region is eliminated.

5.2 Research Limitations

5.2.1 Fare payment structure and dwell time modeling. The major limitation of this study is the possible inconsistency in data format of different transit agencies. For example, the APC dataset is already connected to the AVL dataset in UTA's system. As a result, each APC observation has the exact geotag from the AVL device. On the other hand, APC and AFC observations must be matched according to the associated time stamp. Other transit agencies may use a different level of connection between these datasets, which requires dissimilar matching and noise cancelation methods.

Another limitation of the presented study is the unaccountability for factors that are not variable in one route such as bus configuration impact on DT. For this purpose, several routes with varying bus configuration must be studied together. Finally, the DT modeling specification was based on multivariate regression for simultaneous boarding and alighting through a single door. However, in reality, the boarding and alighting happens simultaneously through two doors (i.e., front and back). This fact has been ignored in our study since the disaggregated APC and AFC data for each door was not available.

5.2.2 Algorithm for dynamic transit accessibility analysis. The main shortcoming of this research is that the PTA is measured only for regions in close vicinity of transit stops. Transit stops as origin and destination locations are probably the best way of measuring PTA. However, the developed PTA measure cannot be directly used for comparison of the PTA with private-car accessibility without geographic manipulation. In addition, the developed algorithm only considers walking for ingress and egress to transit stops, while ignoring cycling and park and ride modes.

5.2.3 Public transit accessibility and transit gap causality analysis. Another main shortcoming of this study is ignoring the PTA measurement for TAZs without transit stops. PTA for TAZs without transit stops can easily be measured by calculating their distance to the closest transit stops. However, such result may not be accurate due to long walking distance. In reality, oftentimes the transit users in those TAZs use a different mode of egress and ingress such as cycling and park and ride.

Another limitation of this study is that the capacity of public transit service was not considered. Ignoring the capacity of service will not impact the presented study since the current level of ridership in UTA’s network is much lower than the provided capacity. However, ignoring the capacity of service may result in overestimation of PTA for mega cities such as New York where the public transit operates almost at capacity in peak periods.

5.3. Future Research Opportunities

5.3.1 Fare payment structure and dwell time modeling. The results of the modeling approach is not the final step in analyzing DT for service efficiency improvements. The next step is to develop and implement policies based on these results and collect the required data (after implementation) to analyze the effectiveness of such policies. Even though a bulk of focus in previous research has been given to analyzing the DT and fare payment structure, the studies on the aftermath of implementing policies on DT management are lacking.

The proposed methodology paves the way for future research on fare evasion estimation by disaggregating transit users according to their fare payment method. For example, the boarding behavior of fare evaders is similar to prepaid pass holders in BRT route 35M MAX. As a result, the number of fare evaders can be estimated by comparing the estimated number of prepaid pass holders from the model and the number of prepaid passes purchased from TVMs. In addition, implementing the proposed modeling approach across various routes in different public transit networks helps analyzing the impact of less studied factors impacting DT such as built environment.

5.3.2 Algorithm for dynamic transit accessibility analysis. The open-source toolbox for the proposed dynamic all-pair shortest path algorithm allows for future improvements, additions, and extensions. There are several improvements that can significantly speed up the algorithm such as data structure techniques and inter-connection of shortest paths finding for different time intervals. Data structure techniques are concerned with finding the best way to store and access GTFS data and travel time vectors. Interconnection of shortest paths finding for different time intervals means preventing the duplicate calculation of in-vehicle travel time for the same origin-destination path that remains constant in two (or more) times of day.

There are couple of possible additions to the algorithm that can improve the accuracy and resolution of the results. Cycling and park and ride as additional ingress and egress modes to transit stop can be planted in the toolbox to improve the accuracy of the PTA results. Such an addition can benefit from the growing research on factors impacting the feasibility and attractiveness of cycling and park and ride modes for ingress and egress to transit stops. Disaggregating the travel time components such as egress/ingress time, in-vehicle time, and transfer time can improve the resolution of the PTA results. Such high resolution allows for exploring the public transit network efficiency and effectiveness. For example, high-resolution transfer time analysis can reveal service incoordination and guide effective schedule development.

Another angle for improving the current algorithm is the use of extensions. A couple of extensions can be added to the toolbox to make it a powerful software for transit network analysis. One important extension can be a visualization package that maps the PTA results on transit network. The current version of the toolbox requires the user to provide the datasets. As a result, accessing the GTFS and census data directly from the web can significantly improve the user-friendliness of the toolbox. Graph analysis is another interesting package that can help with measuring the centrality indices of the public transit network, which is an important component of ongoing network design and analysis research.

5.3.3 Public transit accessibility and transit gap causality analysis. In this study, we were concerned with the equality of PTA and thus gave higher weight to low-salary jobs and low-income workers in measuring the potential opportunities and NPTS. Transit agencies may have additional concerns in PTA analysis such as maximizing ridership and revenue. The next logical step is to explore different ways of jointly using multiple PTA measures following various goals of transit agency, and provide the best solution that addresses these goals simultaneously.

Another interesting research direction is to utilize data mining techniques to enhance the analysis of time series of PTA across transit stops. For example, performing pattern matching for categorizing transit stops based on their PTA can help identify the mismatch between existing and expected transit services. Clustering transit stops based on their associated PTA distribution throughout the day can provide insights on geographic location, quality of service, and service incoordination impact on PTA.

Finally, the proposed research is just the starting point in addressing the issues in dynamic PTA interpretation and transit gap causality analysis. Plenty of testing are still needed in this field to develop a solid method that can address key issues such as normalization independent of outliers, capturing the causality of transit gap, a geographic standardization without loss of accuracy, and trade-offs between resolution and computation speed.