Equity of transit connectivity in Tennessee cities

Abstract

Federal and state agencies focus on providing captive users in mobility-vulnerable population groups with access to public transit resources. One challenge to the provision of equitable access is quantifying equity-oriented metrics for public transit service. This paper utilizes an approach that utilizes the available spatial demographic data and transit network characteristics to compute multimodal transit connectivity and equity. This method is exemplified by analyzing transit connectivity for three metropolitan cities in the state of Tennessee in the United States and overlapping that connectivity on demographic data. Results indicate that the distribution of transit services among vulnerable populations varies within and between cities. The case studies illustrate how this methodology can be used by public agencies to assess the performance of transit systems and to identify the distribution of these systems among various groups to improve the equity of transit connectivity.

Keywords: Public transit, connectivity, equity, Gini index, open-source data

1 Introduction

This paper provides a metric for calculating the connective power of the lines and stops in a public transportation system—and the level of equity inherent in the distribution of those connective resources—using publicly available data. The presented approach focuses on identifying pockets of vulnerable populations within the network area using census data and evaluating the strength of the public transit resources in those areas using General Transit Feed Specification (GTFS) data. Vulnerable populations are, in this case, identified as those possessing low household income or low levels of vehicle ownership, though the methodology presented here could be extended to explore other factors associated with vulnerable or marginalized groups.

Past studies have shown that vulnerable population groups (such as minority or low-income citizens) exhibit higher-than-average needs for transit services (Golub et al., 2013; Sanchez, 1999). In urban environments, these residents tend to be captive transit riders—that is, they often have few transportation resources available and are forced to use public transportation to meet their mobility needs. For all people, reliable access to the essential public and private facilities such as employment centers and medical facilities is vital; for captive riders with few travel choices or heightened barriers to transportation, public transit may be the only viable means of accessing these services. In order to provide access to these facilities, and because mobility correlates highly with economic opportunity (Banerjee et al., 2012; Schweitzer and Valenzuela, 2004; Taylor and Ong, 1995), healthy cities often seek to provide these groups with access to public transportation. However, identifying these groups and quantifying their access to transit can be data-intensive and expensive: these measures are often determined using transit assignment models and ridership tracking tools that are not available to small- or mid-sized cities. As such, the development of reliable performance metrics using open-source data holds value for the transit agencies in these cities.

A transit network represents complex interactions of nodes (stops), and links (routes) with unique characteristics serving various origins and destinations. Frequency, speed, and capacity are critical terms that define the characteristics of a stop or transit route and contribute to conventional transit level-of-service

(LOS) evaluation. The evaluation of transit supply and demand requires a systematic representation of network elements and operational characteristics. A number of connectivity measures are available in the literature, including degree centrality, eigenvector centrality, closeness centrality, and betweenness centrality (Bonacich and Lloyd, 2001; Estrada and Rodríguez-Velázquez, 2005; Mishra et al., 2012; Ruhnau, 2000). However, such measures only consider network-level characteristics and ignore operational characteristics. This paper utilizes a graph theoretic transit connectivity measure that relies on General Transit Feed Specification (GTFS) data coupled with population and employment data to capture the connective power of each stop, line, and traffic analysis zone (TAZ) in a public transit network. Then, equity of transit connectivity distribution is analyzed using the Gini index and census data. These metrics for connectivity and equity are explored in each of the three major cities in Tennessee (TN).

The remainder of the paper is structured as follows. Section 2 presents a review of relevant literature, a summary of gaps in the literature, and the objectives of this study. Section 3 presents the data requirements for the connectivity and equity analysis demonstrated in this paper. Section 4 presents the methodology used to find connectivity and equity and includes a small-scale demonstration and sensitivity analysis. Section 5 shows the results of several numerical experiments for each of the cities included in this case study, and the final section concludes the paper.

2 Literature Review

There is a need in many communities and an interest by most urban planning agencies (TDOT, 2015) to provide better transit alternatives to single-occupancy vehicles using programs and models that do not require transit assignment models or ridership tracking tools. At the same time, ethicists are taking an increased interest in the achievement of social inclusion (Van Wee, 2011) and environmental justice (Rowangould et al., 2016) through the equitable distribution of public resources, including transit provision. In the following paragraphs, this paper reviews current literature pertaining to transportation network connectivity metrics, measures of equity and current practices of transit agencies towards incorporating equity impacts in the transportation investment decision-making.

2.1 Measures of Supply

In the previous literature, the transit supply has been measured using three different approaches namely mobility, accessibility and connectivity. In this section, we provide the definition, capability and limitation of such approaches.

2.1.1 Mobility

Mobility measure captures the ease for a potential rider to travel in a particular area using existing transit services and is calculated based on the service frequency on a node or transit station (Sanchez et al., 2004), number of vehicle miles (Buehler, 2009). However, mobility measure only provides a quantity of travel activity and includes the limitation of not measuring service quality.

2.1.2 Accessibility

Accessibility, being an essential dimension of public transit services, has been studied heavily in past literature to quantify the efficacy of transport networks (Martínez et al., 2016) and is usually applied to a single node or station in a network. In past literature, accessibility measures are divided into three different categories: location-based, transport capacity-based, and potential-based ((Ato) Xu et al., 2018). Location-based accessibility (LBA) measure captures the ease of reaching a station or node and referred to as "access," "local Accessibility and "to-transit accessibility" (Geurs and Van Wee, 2004; Matisziw and Grubesic, 2010; Moniruzzaman and Páez, 2012). LBA is calculated based on average cost or travel time to reach a transit node (Karou and Hull, 2014). Potential-based accessibility (PBA) captures the possible maximum passenger demand a transit service can serve in a specified area (Cui et al., 2016; Moniruzzaman and Páez, 2012) and also referred as "locational access," "regional accessibility" and "by-transit accessibility" (Moniruzzaman and Páez, 2012; Páez et al., 2012). PBA is estimated from a function of travel demand in a specified area and anticipated travel cost for other adjoining areas from this area (Hansen, 1959), where travel cost can be represented in terms of money, time or distance. Transport capacity-based accessibility (TCBA) captures the ease of travel activity of passenger demand in a transit service under different constraints like environmental characteristics and service level attributes and is estimated from user behavior, usually employing utility-based methods (Nassir et al., 2016). Martens (2016) developed a theoretical framework for establishing a threshold for sufficient accessibility.

Other measures of measuring transit supply, similar to accessibility, include measuring the density of transit service (Currie and Wallis, 1992), public transportation accessibility level (PTAL), obtained from different transit stop characteristics, including walking and average waiting times, service frequency and reliability, (Wu and Hine, 2003) and transit supply index (TSI) (Bertolaccini and Lownes, 2013), calculation similar to transit service density. However, such measures do not include all the transit service characteristics and destinations connected to the transit services.

2.1.3 Connectivity

Connectivity measure is a blend of both mobility and accessibility measures (Hadas and Ranjitkar, 2012; Kaplan et al., 2014; Welch and Mishra, 2013), which evaluates the level of service for a public transit network and captures the ease of connection between different nodes in a transport network (Cheng and Chen, 2015). Connectivity can be calculated in terms of time (in-vehicle, waiting, access/egress), frequency, service reliability, and transfers along multimodal routes on a transit network (Kaplan et al., 2014). Also, the previous literature has regarded the connectivity befitting index to evaluate PBA (Suau-Sanchez and Burghouwt, 2012; Van Wee, 2016). Since the Connectivity index usually requires real travel costs and time between different locations in the networks, its application in evaluating a transit network is limited ((Ato) Xu et al., 2018). Connectivity measure outperforms accessibility and mobility measures in terms of incorporating transit service characteristics.

Exploration of network connectivity has not been limited to measures based on connective power; degree centrality, eigenvector centrality, and betweenness centrality have all been thoroughly addressed (Ahmed et al., 2006; Bell et al., 1999; Bonacich, 2007; Bonacich and Lloyd, 2001; Carrington et al., 2005; Estrada and Rodríguez-Velázquez, 2005; Freeman, 1978; Garroway et al., 2008; Guimerà et al., 2005; Junker et al., 2006; Liu et al., 2005; Martínez et al., 2003; Moore et al., 2003; Newman, 2004; Ruhnau, 2000). Degree centrality measure captures the number of nodes connected to a particular node in the network but ignores the connection quality. Eigenvector centrality overcomes this limitation after assigning "scores" proportional to the connecting power of the nodes. Node closeness centrality captures the graph-theoretic distance in the form of shortest distance from the other nodes and hence nodes with low closeness scores are highly accessible. Betweenness centrality measures capture the time required to utilize a particular node to make a transfer between two other nodes. However, all centrality measures do not account for transit characteristics and rely entirely on network characteristics.

In summary, the use of connectivity measures in transit services has evolved. Park and Gang (2010) developed a quantitative model for multimodal urban transit network connectivity. The authors identified line length, speed, and capacity as key components of a transit line's utility, then defined its connecting power as the product of those components. The blend of spatial parameters with operating parameters in Park and Gang's work sparked interest in graph-theoretic measures of transportation network connectivity and was later expanded by Mishra et al. (2012) to include connectivity measures for transit stops and transfer centers. Welch and Mishra (2013) further expanded these measures to include zone connectivity measures, utilizing the concept of catchment areas around transit stops, and linking connectivity to equity. Mishra et al. (2015) developed a tool for visualizing the geographic distribution of connectivity, while Sarker et al. (2015) explored alternative scaling coefficients for use with these connectivity measures. Hence in this study, we explore the connectivity measure which includes transit characteristics through the publicly available dataset.

2.2 Equity

In the previous literature, the terms "equality" and "equity" are used synonymously, corroborating to confusion as they both have different meanings, especially in public transit context. The equality concept is similar to "being equal" or "sameness," which contends that if the people and groups have the same opportunities and rights, they should be treated equally. In public transit context, this would mean to provide the same level of services to the entire population which is not generally the case. Hence, equality, in practice, is not the objective and impractical (Carleton and Porter, 2018). Equity, on the other hand, implies that since not all people and groups have the same opportunities, they should not be treated another way to make up for the different opportunities (Brick, 2015; Litman, 2016). Hence, equity implies “justice” or “fairness,” which tends that not the entire population relies on public transit facilities and the ones who use these services more than others should be given priority over others, which ultimately makes sense.

In past literature, there is no consensus on a single definition of equity (Bills and Walker, 2017; Levinson, 2010; Thomopoulos et al., 2009). In terms of regional planning agencies, Bullard (1994) defines three different types of equity, i.e., procedural, geographic, and social. Procedural equity deals with process-specific factors, including time, location, and language of public meetings. Geographic and social equity deal with the spatial and demographical distribution of costs and benefits. In past studies, social equity is further classified into two different types, i.e., horizontal and vertical (El-Geneidy et al., 2016; Musgrave et al., 1989; Welch, 2013). Horizontal equity implies providing proportional transit facilities among the population with similar socioeconomic characteristics. Vertical equity, on the other hand, suggests a different distribution of transit facilities among different population groups.

In addition to definition and different types of equity, past literature defines different standards or principles for evaluating equity-like Pareto, utilitarianism, egalitarianism, Rawls-egalitarianism, and many more (Pereira et al., 2017). For instance, Rawls-egalitarianism refers to prioritizing the least advantaged population for distributing benefits, whereas utilitarianism deals with maximizing the benefits for the entire population (Pereira et al., 2017; Van Wee and Geurs, 2011). Lucas et al. (2016) and Pereira et al. (2017) provide a useful discussion of the two non-utilitarian ethical approaches to accessibility: egalitarianism and sufficientarianism . While egalitarianism suggests that accessibility should be distributed equally regardless of need or outcome, sufficientarianism suggests that resources should be preferentially distributed in such a way as to bring all individuals (or groups) up to some minimum level of accessibility.

2.2.1 Measure of Equity

Social exclusion, environmental justice, and accessibility are roundly discussed in modern ethical theory. In his 2011 book, Van Wee shows that traditional cost-benefit analysis (CBA) is often insufficient for addressing the exclusion of vulnerable groups, and can lead to inequitable distribution of public resources. This inequitable distribution is at odds with the Civil Rights Act of 1964 (Civil Rights Act, 1964). In practice, the equity analysis falls under two different approaches, i.e., modeling and non-modeling approach (Bills and Walker, 2017). The modeling approach includes exploring the equity impacts through regional travel demand models (Bills and Walker, 2017; J. Ding et al., 2018; Ramjerdi, 2006) in contrast to non-modeling approaches, which include equity analysis through the use of spatial analysis tools (Currie, 2010a, 2004; Delbosc and Currie, 2011). Non-modeling approaches are more prevalent among metropolitan and transit planning agencies (Amekudzi et al., 2012). (Bills and Walker, 2017) analyzed equity in transportation improvements using a revealed preference survey data, activity-based travel model, equity standards defined in past literature, and consumer surplus as equity indicator.

In the past literature, in non-modeling approaches, equity is measured mainly through Gap analysis (Currie, 2010b; Fransen et al., 2015) and Lorenz curves coupled with Gini coefficients (Delbosc and Currie, 2011; Kaplan et al., 2014; Welch and Mishra, 2013). Gap analysis, also known as the "needs gap," illuminates a distinction between transit supply and potential demand for specific population groups. Currie (2010 & 2004) measured the spatial distribution of public transport empirically extending their previous research (Currie and Wallis, 1992) to calculate transport needs and using gap analysis for transportation disadvantaged (Currie, 2004) and socially disadvantaged (Currie, 2010a) population.

Gini coefficients derived from Lorenz curves, on the other hand, deduce the deviation of cumulative distribution transit supply provided to specific population groups from perfect equality (sometimes denoted as equity in literature). Gini index evaluates the distribution of a particular indicator or an attribute among the population with values of 0 and 1 reflecting perfect equality and inequality, respectively. Gini index results in an inequality measure that is independent of demand and scale (Bertolaccini and Lownes, 2013; Yeganeh et al., 2018). One of the advantages of using Gini coefficients over gap analysis is that Gini coefficients give the sense of transit equality for the entire area, whereas gap analysis results in spatially dependent analysis. However, with Gini coefficients, additional analysis is needed to get the spatial implications of equality because of the spatially disassociated results (Carleton and Porter, 2018).

Delbosc and Currie (2011) assessed equity for public transport in Melbourne using Lorenz curve cum Gini coefficients based on the distribution of public transport index, developed from databases of transit stops, among population and employment opportunities (obtained from census dataset). However, the public transport index did not include the service characteristics of public transit. Bertolaccini and Lownes (2013) studied the effect of geographic boundary and scales on equity assessment using the Gini index while using the TSI measure of supply and GTFS data and concluded that Gini index equity results are unaffected by scale and demand. Welch and Mishra (2013). take a different approach, calculating the Gini index (Gini, 1936) for the distribution of connectivity against socioeconomic identifiers such as income and car ownership. This approach is unique in that it can illustrate the level of horizontal equity extant in the system as well as measuring both subtypes of vertical equity.

Yeganeh et al. (2018) analyzed the social equity for 45 public transportation systems in the US based on job accessibility using publicly available datasets, census, and transit-job accessibility, accessibility indicators, and Gini index. Results showed higher job accessibility for low-income and non-white individuals. Ding et al. (2018) analyzed the equity for bus transit networks using in Beijing using Gini index based on transit accessibility index, estimated from attractiveness (transit service level of stops) and reachability (impedance function), embedded in gravity-based travel demand. However, this study did not use open-source transit data and non-modeling techniques.

2.3 Equity practices in planning agencies

In this section, we explore past studies on common practices of transit agencies on incorporating equity in transportation investment decisions. Majority of transit agencies employ cost-benefit analysis (CBA) to prioritize transportation investments (Joshi and Lambert, 2007; Thomopoulos et al., 2009) and include limitations in terms of not considering equity either with inappropriate definitions (Taylor and Morris, 2015) or not analyzing equity impacts at disaggregate levels (Bills et al., 2012; Linovski et al., 2018; Manaugh et al., 2015).

Joshi and Lambert (2007) developed a method for modifying traditional CBA to include a weighted measure for equity. Thomopoulos et al. (2009) provided a review of existing equity practices in transit infrastructure evaluation along with their limitations and proposed a new methodology to eliminate the identified limitations of CBA and multi-criteria analysis (MCA) were the most commonly used methodologies to study equity impacts in transportation investments especially in Europe. CBA methods, which involve selecting the project with the highest benefit-cost ratio (BCR), include limitations in terms of considering aggregate welfare (ignoring equity impacts), inability to capture intangible factors and non-monetary impacts and discount rate selection. In contrast, the MCA approach, which involves combining multiple attributes with different values to prioritize transit investment, overcomes the limitations of CBA. However, MCA includes limitations in terms of biased decision-makers which affects the weights given to different attributes in decision making process.

Bills et al. (2012) show that activity-based long-range transportation plans fail to account for the differences in travel habits between different groups of interest. Similarly, Manaugh et al. (2015) analyzed long-range planning documents of 18 different North American metropolitan areas for the consideration of social equity. The authors highlighted the absence of a clear and meaningful definition of social equity, inadequate disaggregated analysis and more focus on environmental impacts than social equity in transit investment decisions. The author highlighted the need to incorporate equity tools and definitions in the planning framework. Golub and Martens (2014) presented an "access poverty" equity assessment approach for transit and automobile accessibility. Taylor and Morris (2015) examined whether public transportation policies prioritize equity impacts based on data obtained from the National Transit Database (NTD), American Public Transportation Association (APTA), National Household Travel Survey (NHTS) and a survey of 50 different transit operators. The results highlighted the income difference between bus and rail transit users, less emphasis on equity impacts in terms of prioritizing vulnerable groups and increased preference to rail transit investments.

Karner (2016) provides a review of equity practices in eight small rural region MPOs in California. In its analysis, the author concludes that each MPO has different definitions and practices for evaluating equity and defining transportation-disadvantaged groups. In all the MPOs, equity was evaluated based on travel demand models and spatial techniques followed by proximity analysis, (distance related directly to utility and benefits) to evaluate an upcoming transportation project. Also, most of the MPOs relied on low-resolution maps to evaluate equity spatially. Hananel and Berechman (2016) proposed a novel framework for incorporating transport justice or equity in the decision-making process while considering capabilities approach and concluded that such a framework is less feasible in urban areas because of the political constraints in place. Linovski et al. (2018) provided an empirical analysis of bus rapid transit investments while focusing mainly on the integration of equity in decision making in three metropolitan regions in Canada. Findings based on the interviews of transit officials and planning documents revealed the rare occasions of integrating equity in transit investment decisions and different definitions of equity in each metropolitan area. Also, the equity was considered for different socioeconomic groups but not for the transit-dependent population and highlighted the need for better understanding and methodologies to incorporate equity into transit investment decisions.

Hence, past literature vindicates the need to incorporate equity in transit planning practices and no approach has utilized publicly available datasets and open source methodologies to explore the equity impacts in transportation investments.

2.4 Research Gaps

Forecasting transportation demand has typically required complex data sources not available to all transit authorities, but the literature reveals a recent push toward the use of more tractable models using open-access data sources. Within the study of equity, many ethicists prescribe a conceptual approach, while fewer practitioners develop methods of applying quantifiable measures of system equity. Therefore, there is room for a study to leverage open-access data to quantify connectivity at the line, node, and zone levels, then to apply tractable metrics to show the geographic distribution of that connectivity in relation to captive riders. Connectivity measure, being a blend of both mobility and accessibility measures, evaluates the level of service for a public transit network and captures the ease of connection between different nodes in a transport network and accessibility and mobility measures in terms of incorporating transit service characteristics. Hence in this study, we employ the connectivity measure to include transit characteristics through the publicly available dataset.

In addition to using open source data to measure transit connectivity at zone, node, and link levels, the Gini inequity index is employed in this study which utilizes operational characteristics of transit to identify the transit distribution among socioeconomic characteristics of the population. One of the advantages of using the Gini inequity index is that Gini coefficients give a sense of transit equality for the entire area. This study also contributes to the existing literature in terms of the effect of change in the characteristics of one line on other lines in the network (sensitivity analysis). The application of the proposed framework to three major cities in Tennessee, to identify equity associated with transit connectivity, contributes to the literature further. Therefore, this study is utilizing the existing methodological framework to identify equity associated with transit services and evaluate different transit plans based on the estimated Gini index values based on the open-source datasets.

2.5 Contribution

Building on the previous literature on measures of supply for transit services, equity measures and existing practices of transit agencies towards incorporating equity in investment decisions, the contribution of this study are threefold: (i) Demonstrate the use of open-source datasets in evaluating equity impacts (ii) Demonstrate the use of simpler, convenient algorithms to compute transit connectivity and equity while utilizing such datasets (iii) Complement transit agencies' investment decisions with most straightforward and easily interpretable equity measure while incorporating transit service characteristics in terms of connectivity.

2.6 Study Objectives

The scope of this study is to (i) apply transit connectivity measures to the multimodal transit networks within the case study areas using open-access data, (ii) associate transit connectivity measures with various captive rider characteristics to determine transit equity, and (iii) summarize transit equity in terms of the distribution of transit services across different groups, based on Gini index, in a format that is useful to local transit decision-makers. Three cities in Tennessee (Nashville, Memphis, and Knoxville) are used as the case study areas.

3 Data Requirements

One of the major benefits of this methodology is that it makes use of open-access data, which decreases the cost to use this measure and makes it accessible to transit authorities regardless of their access to transit ridership models or tracking tools.

3.1 GTFS Data

GTFS data (Open Mobility Data, 2016) is the primary data source used in this method to analyze connectivity. GTFS data is an open-access source that presents information on fixed transit routes in a standardized format (Antrim and Barbeau, 2013). This methodology uses it to identify transit lines, stop locations, operating schedules, and other line characteristics such as speed and capacity. It should be noted that GTFS does not include information on demand-responsive transit (DRT) services such as paratransit; as a result, this study neglects DRT.

3.2 Zonal Information

In Tennessee, the statewide travel demand model contains information about employment by TAZ. While other states may aggregate employment across different types of areas (i.e., census blocks, census tracts, or TAZs), each state provides this information in an open-access format. Employment information is used in calculating the connectivity index, while the study area is divided into TAZs to add granularity to measures of equity.

3.3 Census Data

Census data (US Census Bureau, 2010) provides information on population, which is used to calculate the connectivity index. The census also provides data on income and car ownership which is used to identify

TAZs with high levels of captive ridership. This information is used to measure the equity of the distribution of transit connectivity.

4 Methodology

This paper modifies the methodology developed by Welch and Mishra (2013) to obtain connectivity indices at the line, node, and zone levels. Then, this paper uses the Gini index with the zone connectivity index to show the distribution of connectivity by income level and by vehicle ownership. The notation used throughout the methodology section is summarized in Table 1. A flow chart illustrates this process in Fig. 1.

--Table 1 here--

--Fig. 1 here--

4.1 Node Connectivity

Node connectivity is defined in order to show the quality of each stop in a multimodal transit network. Connectivity for each node is derived from the connective power of the transit lines incident upon that node and scaled for desirability as compared with other nodes in the system. First, the connecting power of the inbound and outbound lines at the node is calculated in Equations (1) and (2). (The reader is referred to Mishra et al. (2012) and Welch and Mishra (2013) for further details about connecting power of nodes and lines).

$$P_{l,n}^{i} = \left[\left(\frac{\alpha_l \times C_l}{100}\right)\left(\frac{\beta_l \times V_l}{100}\right)(\gamma_l \times D_{l,n}^{i})(\varphi_l \times A_{l,n})\right] \tag{1}$$

$$P_{l,n}^{o} = \left[\left(\frac{\alpha_l \times C_l}{100}\right)\left(\frac{\beta_l \times V_l}{100}\right)(\gamma_l \times D_{l,n}^{o})(\varphi_l \times A_{l,n})\right] \tag{2}$$

Where, C_l, V_l and $D_{l,n}$ are transit characteristics, average capacity, speed, and route distance from node n to the destination respectively, for line l. $A_{l,n}$ represents the activity density which measures opportunities accessible at each transit node and can be estimated as the ratio of the total number of households and employment in a zone to the total area of the zone.

The scaling coefficients (α, β, γ, and φ) indicate the attractiveness of one line compared to other lines in the system. Each coefficient is calculated under the assumption that its related parameter (capacity, speed, distance, and activity, respectively) follows a normal distribution. For example, the determination of β_l requires the assumption that $V \sim N(\mu_V, \sigma_V^2)$ as shown in Equations (3) and (4). The same is true for the other coefficients.

$$p(V) = \frac{1}{\sigma_V \sqrt{2\pi}} e^{-\frac{(V-\mu_V)^2}{2\sigma_V^2}} \tag{3}$$

$$\beta_l = p(V < V_l) = \int_0^{V_l} \left(\frac{1}{\sigma_V \sqrt{2\pi}} e^{-\frac{(V-\mu_V)^2}{2\sigma_V^2}} \right) dV \tag{4}$$

Activity, if accurately quantified, represents diverse classification groups of households, population, employment, and built environment characteristics (Bhat and Guo, 2006). However, as per previous literature, activity is represented in different contexts such as entropy, density, etc. (Bhat and Guo, 2006; C. Ding et al., 2018; Ding et al., 2017; Ding and Cao, 2019; Pinjari et al., 2009). For instance, in the trip generation stage, specific trip rates are defined based on activity type, where activity type is defined as a combination of population and employment densities. Similarly, in the built environment, entropy is used as a proxy for activity diversity. For simplicity, land use or built environment characteristics are represented by the proxy variable activity density, defined in Equation (5). Hence, activity density is the average number of jobs and households within the zone (TAZ) in which the transit node is located.

$$A_{l,n} = \frac{H_{l,n}^z + E_{l,n}^z}{\Theta_{l,n}^z} \tag{5}$$

However, in transit connectivity context, the definition of activity is only a proxy represented by density, and it does not describe low versus high-income behavior or residential versus commercial usage which contributes to the limitation of this approach. Once the connective power of the incident lines has been calculated, the connectivity index for each node is calculated as the average connecting power of all lines passing through that node, as shown in Equation (6).

$$CI(n) = \frac{\sum_{l} \frac{P_{l,n}^{i} + P_{l,n}^{o}}{2}}{\Theta_n} \tag{6}$$

4.2 Line Connectivity

Once node connectivity is established, line power is averaged across the line and scaled by the number of stops, as shown in Equation (7). This scaling allows comparison between lines with many stops (such as bus lines) and lines with few stops (such as light rail lines).

$$CI(l) = \frac{\sum_{n \in S_l} \frac{P_{l,n}^{i} + P_{l,n}^{o}}{2}}{|S_l| - 1} \tag{7}$$

For a step-by-step demonstration of the calculation of node and line connectivity, see Table 2.

4.3 Catchment Areas and Zone Connectivity

Kim et al. (2005) developed a distance-decay function (shown in Equation (8)) for passenger acceptance of transit stops based on the walking distance to the stop. The coefficients they estimated are based on empirical data and are exacting to capture walk distance to transit stops. Therefore we have assumed the same coefficients for this study (τ = 1.3189, λ = -0.0872) (Kim et al., 2005). For each housing unit, a half-mile catchment area is created, in keeping with results from Kim et al. (2005). For each node within the catchment area, the distance decay function (Equation (8)) is computed (nodes outside the catchment area receive a score of zero from that housing unit). Once the function has been computed, a prorated score for each node is determined by aggregating the score it receives from each housing unit. Finally, the zone score is taken as the average of the prorated node scores, as shown in Equation (9).

$$\rho_{h1,n} = \tau e^{\lambda t_{h1,n}} \tag{8}$$

$$\theta_z = (|S_z| - 1)^{-1} \sum P_{l,n}^{t} (\rho_{h1,n}) \tag{9}$$

4.4 Small-Scale Example and Sensitivity Analysis

In this section, we apply the proposed methodology in an example transit network for calculating connectivity (Fig. 2). The nodes are connected by four bi-directional transit lines. For simplicity, both directions of each transit line have the same properties; therefore, $P^i_{l,n} = P^o_{l,n} = P^t_{l,n}$. In a real network, this is likely to be the case for some transit lines, but not all. Input data for each transit line are shown in Fig. 2, while Table 2 demonstrates the application of Equations (1-5). Results are shown in Table 3, and demonstrate the application of Equations (6-7).

The left set of columns of Table 2 shows input data for each line at each node, where hourly capacity is the product of frequency and unit capacity. For each of the four key inputs (distance, speed, hourly capacity, and activity density), the mean and standard deviation are calculated. Then, Equations (3-4) are applied to calculate α, β, γ, and φ for each line's distance, speed, hourly capacity, and activity density, respectively. For this example, all distributions have been assumed normal for simplicity; if parameters in a real network follow another distribution, the related equations can be substituted for Equations (3-4). Line power is calculated using Equations (1-2).

--Fig. 2. here--

--Table 2 here--

The final results (Table 3) show the application of Equations (6-7). Results show line 1 as the most powerful followed by line 2 justified by the longer route length supported by attractive characteristics of these lines. Similarly, node 2 emerged as the most powerful followed by node 1 as both of these nodes are connected to line 1 and line 3. Line 2 emerged the least powerful followed by line 4 because of their small route length. Therefore node 4 has the least connecting power as it is connected to line 4 only.

--Table 3 here--

4.4.1 Sensitivity of Scaling Coefficients

The example network can be used to demonstrate the sensitivity of the scaling coefficients. As each parameter on a given line changes, the mean and standard of deviation for that parameter change for the entire network; this change indicates a shift in the desirability of one transit line as compared to the others. This nonlinear interplay is shown using speed as the example parameter. Keeping all other variables constant, the speed of line 1 was incrementally increased from 0 to 50 (units here are unimportant, so long as the same unit is used for each transit line). The resulting influence on the speed scaling coefficient (β) is shown in Fig. 3.

The beta value for line 1 follows the cumulative normal distribution, moving from low importance to high importance. Beta values for lines 2 and 4 are inversely related and share a similar inflection point. The implication is that within certain ranges, improvements in one line may generate improvements in the attractiveness of other lines; however, as the speed of one line begins to dominate the network, the attractiveness of all other lines falters. This analysis also highlights the fact that connectivity scores are relative: they can be used as a means of comparison between lines and nodes in the same network, but cannot be used to compare lines across different networks.

4.4.2 Model Sensitivity

Connectivity of each node and each line were monitored as parameters for line 1 were changed. Results reveal differences in the way line connectivity and node connectivity, each response to network changes. As each parameter for line 1 increases, connectivity for other lines shows a slight increase, followed by a prolonged decrease, shown in Fig. 4. As the capacity of line 1 increases, connectivity of lines 2 and 4 falls 53.8% and 54.2%, respectively. As activity along line 1 increases, connectivity of lines 2 and 4 each fall 64%. These changes reflect the same pattern shown in Fig. 3. Node connectivity, however, reacts differently.

--Fig. 3. here--

As the connecting power of a line increases, the nodes connected by that line see an increase in connectivity. However, nodes not connected by that line show a decrease in connectivity. This again reflects the change in attractiveness; nodes with a high-powered line are more attractive to riders than nodes with low-powered lines. Fig. 4 shows the changes in line and node connectivity as parameters for line 1 are changed individually; Fig. 5 shows the changes in the connectivity of each line as the speed and capacity of line 1 are allowed to vary simultaneously. Note the different scales used in each sub-figure.

--Fig. 4. here--

-- Fig. 5. here--

4.5 Measuring Equity

The Lorenz curve measures the distribution of a particular attribute with respect to the considered socioeconomic characteristics, in this case, transit connectivity for every cumulative percent of the population, vehicle ownership, and household income. When perfect resource equity is achieved, the Lorenz curve is a straight line; each additional 1% of the population controls an additional 1% of the resource. The Gini index shows the areal difference between the Lorenz curve and the perfect equity line; a Gini value of zero shows perfect equity, while a Gini value of one shows perfect inequity. The formula for calculating the Gini index is shown in Equation (10).

$$G_s = 1 - \sum_k (X_k - X_{k-1})(Y_k - Y_{k-1}) \tag{10}$$

For each of the cities in the case study, the connectivity of each zone was calculated and compared to the average household income, average vehicle ownership, and population within each TAZ. In each city, the Gini index was calculated across each of these three categories. For further insights into the calculation of Gini index, refer to prolific past literature (Cowell, 2011; Farris, 2010; Handcock and Morris, 2006; Thomas et al., 1999).

5 Case Study Results

The presented methodology was applied to case studies in three cities in Tennessee: Memphis, Nashville, and Knoxville and their location is shown in Fig. 6. Location of three case cities Knoxville, Memphis and Nashville. . In each city, public transit options are limited to buses and trolleys, with on-call paratransit options. Bus rapid transit services are available in Nashville, but not in Memphis or Knoxville. Demographic information for each city—as well as the state and nation—are given in Table 4, and based on the July 1, 2016 estimates from the US Census Bureau (2017).

--Fig. 6. here--

--Table 4 here--

A map for each city and category (household income, vehicle ownership, and population) is presented to help visualize results. For example, Fig. 7 shows three such maps for all three case cities. Fig. 7(a) portrays Memphis transit line connectivity and vehicle ownership. Each TAZ is grayscale-coded to show the level of vehicle ownership, where the light shade of gray indicates zones with low vehicle ownership, and darker shade of gray indicates zones with high vehicle ownership. Overlaid atop the TAZs are the transit lines in the city. Transit line connectivity is shown in terms of a heat map where different color indicates the density of transit line connectivity varying from low to high. Thin, pink lines indicate transit lines with low connectivity, while thick, blue lines indicate transit lines with strong connectivity. Fig. 7(b) shows Nashville's transit line connectivity density and population density. Light shades of gray indicate TAZs with low population density, while darker shades of gray indicate TAZs with higher population density. Fig. 7(c) shows the Knoxville's stop connectivity density and household income. Transit stop connectivity is also represented in terms of density for each stop node; different colors indicate variation in transit stops with low connectivity to transit stops with higher connectivity. Following these formats, Fig. 9 (a), (b), and (c) in the Appendix shows Memphis's transit stop connectivity density with household income, Nashville's transit stop connectivity density with household income, and Knoxville's transit line connectivity with vehicle ownership, respectively. Each image gives local transit authorities information on which stops, and lines are underperforming, as well as which areas of the city demonstrate high levels of captive ridership.

The maps, shown in Fig. 7, and Fig. 9, give visual information on the geographic distribution of connectivity but do very little to show the equity of that distribution. Showing equity requires more processing and requires the aggregation of zones based on characteristics of the populations in those zones. To this end, Tables 5-7 give the distribution of zonal connectivity across varying levels of household income, vehicle ownership, and population density, respectively. For each city, four columns are presented: the first shows the percentage of the population falling into each group; the second shows the raw connectivity score available to each group; the third shows the percentage of the network's total connectivity score available to each group (Equation (11)); the fourth shows the ratio of the percent of available connectivity to the percent of the population in each group (Equation (12)). Under a system in egalitarian perfect vertical equity, each element of the connectivity-to-population ratio would equal 1. In each table, shaded rows indicate the groups with access to the largest percentage of the network's connectivity, while rows in bold indicate the groups with the highest connectivity-to-population ratio.

$$\%\ Connectivity_i = \frac{Avg\ Connectivity_i}{\sum_i Avg\ Connectivity_i} \tag{11}$$

$$\%\ Conn\ to\ \%\ Pop_i = \frac{\%\ Connectivity_i}{\%\ Population_i} \tag{12}$$

--Fig. 7(a). here--

--Fig. 7(b). here--

--Fig. 7(c). here--

5.1 Connectivity with Household Income

Household income was broken down into nine categories, each with a $20,000 range. The average household income for each zone was calculated from census data and compared with zonal connectivity scores. The result is shown in Table 5.

Across all three cities, high income is correlated with high levels of connectivity. Knoxville is a notable exception in that the lowest income group exhibits the second-highest level of connectivity; this phenomenon is due to high connectivity scores on the University of Tennessee, Knoxville's campus and housing districts (Fort Sanders area). The connectivity-to-population ratio bolsters the observation that high income correlates to high levels of connectivity; in all three cities, the highest per-capita connectivity is experienced by the highest earners.

--Table 5 here--

In Memphis, this trend is due to the low connectivity scores associated with the nexus of low income and low connectivity exhibited in the Raleigh, Frayser, Airport Industrial Area, and West Memphis communities, coupled with high property values along the well-connected Poplar Avenue corridor. Nashville transit exhibits high connectivity around the high-income Belle Mead and Bellevue districts but shows low connectivity near the river in low-income North Nashville. In Knoxville, high-connectivity lines stretch into the high-income Sequoyah Hills and Woodland Acres neighborhoods, while low-connectivity lines serve low-to-middle-income North Knoxville and South Knoxville neighborhoods.

5.2 Connectivity with Vehicle Ownership

For each zone, vehicle ownership was defined as either No vehicles, low (1 vehicle per household), moderate (2 vehicles per household), or high (> 2 vehicles per household) using census data. Vehicle ownership was compared with zone connectivity and shown in Table 6. Shaded rows indicate the groups with access to the largest percentage of the network's connectivity, while rows in bold indicate the groups with the highest connectivity-to-population ratio.

--Table 6 here--

Distribution of connectivity with vehicle ownership varies more widely from place to place than distribution with income; each city grants the largest portion of its available connectivity to a different group. Nashville provides the greatest connectivity to zones with low vehicle ownership, Memphis to zones with moderate vehicle ownership, and Knoxville to zones with high vehicle ownership. In this case, however, distribution in every city is more aligned with a sufficientarian perspective: in all three cities, the highest connectivity-to-population ratio is found amongst the lowest vehicle ownership group. It is worth mentioning that in both cities, the population with no household vehicles had the highest connectivity to population ratio which reflects the consideration of respective transit agencies to captive riders. Although Knoxville includes no population with zero vehicle ownership, similar findings are found in the low vehicle ownership. Of the three cities, Nashville's transit distribution exhibits the strongest preference toward low vehicle ownership zones.

It is worth noting that the highest average connectivity levels and highest connectivity to population ratio differed among vehicle ownership groups, which can be either due to the less proportion of the population of low vehicle ownership groups or high-income individuals living in urban areas having high transit connectivity. However, it is not clear from the comparison of connectivity with the population. Therefore we expand Table 6 to include average household income in each vehicle ownership group in

Table 7. This inclusion reflects the impact of the built environment and household income on vehicle ownership (Bhat and Guo, 2006). Hence, Memphis and Nashville reflect high-income individuals involved with no vehicle ownership whereas in Knoxville, low-income households are associated with low vehicle ownership. Hence, high connectivity to population ratio in Memphis and Nashville can be regarded as the population living in the dense urban areas whereas in Knoxville, it can be regarded as less population proportion with low vehicle ownerships.

--Table 7 here--

It should be noted that these results are likely to be self-reinforcing: transit authorities often attempt to connect households with low vehicle ownership to important destinations, and adjacency to well-connected public transit is likely to encourage low vehicle ownership. This cycle may be desirable for transportation agencies interested in decreasing the number of trips made in single-occupancy vehicles (TDOT, 2015). As these cities gentrify and urban cores repopulate with higher-income residents (who may have lower vehicle ownership), a disconnect between income and vehicle ownership may develop, especially in areas with strong public transit connections. As a result, tracking both these variables may continue to provide insight into the evolution of captive ridership.

5.3 Equity

For each city, the Gini index was calculated for each category. The Lorenz curves are portrayed in Fig. 8, and the Gini index results are shown in Table 8. For each category, an asterisk indicates the most equitable system. The Gini index indicates the equity between groups, and seeks to answer the question: “Does each group have equal access to public transit connectivity?” As such, the Gini index is blind to the differences between groups, including a group level of need. A high Gini index indicates that only a small group disproportionately controls connective resources; it does not imply that those resources are controlled by an otherwise privileged group such as high earners or groups with high vehicle ownership. It is therefore important to note that the Gini index should be taken in context with the preceding discussion and not used as the sole metric for equity.

Of the three cities in the case study, Memphis shows the least preference for one group over another in terms of household income; i.e., it provides more egalitarian connectivity on household income than other cities. Knoxville is close to Memphis in terms of the least equality of connectivity with household income. Nashville is close to perfect inequality with a value of 0.64 for the distribution of connectivity with household income. However, Nashville is close to perfect equality in terms of household vehicle ownership. Nashville's system tends to be more sufficientarian than egalitarian in terms of distributing connectivity among the population and household income because of the higher Gini index scores. Knoxville includes the most equitable distribution of connectivity in terms of population. All three cities show high levels of inequity across vehicle ownership and population and show moderate levels of inequity across income. In order to improve equity in accordance with the Civil Rights Act of 1964 (Civil Rights Act, 1964), each city should direct more connective resources to low-income areas.

It is worth mentioning that the objective of this study is not to conclude that whether the distribution of transit services in three different cities is good or bad but to complement different plans and targets of transit agencies. For instance, if the transit agency plans to provide high-quality transit service to Nashville's population, then the agency should focus on decreasing the inequality score towards perfect equality. However, if the transit agency in Memphis plans to provide increased coverage to low-income households, the target should be to increase the Gini index towards perfect inequality. Similarly, the existing Gini index scores for vehicle ownership reflect a differential treatment of different vehicle ownership groups and no modification is required if the aims are to prioritize transit captive riders over others. Similarly, Lorenz curves presented in Fig. 8 can also be utilized to evaluate the plans with the target of increasing or decreasing the area under the Lorenz curve depending upon the objectives.

--Fig. 8. here--

The population proportion with low vehicle ownership in almost all three cities is at most 8% (reflecting low proportion of transit captive riders) which indicates the need to consider an egalitarian principle to provide a high-quality transit service to all vehicle ownership groups or population or providing a transit service with a Gini score close to perfect inequality in case or dense urban areas. However, additional analysis may be required to evaluate such plans as the Gini index are incapable of providing spatially associated results (Carleton and Porter, 2018).

--Table 8 here--

6 Conclusions and Policy Implications

Transit connectivity is a multidimensional problem involving various service quality factors that include both operational and geographical parameters. Furthering this complexity is the (usually) high number of available routes with distinct characteristics within a network. Because budget constraints limit the capacity of many transit agencies to develop a travel demand model or to maintain detailed ridership data, there is a need for transit models that do not require complex data (e.g., onboard surveys Karner and Golub (2015)). This study leverages existing transit network connectivity indices that work solely on open-source data to evaluate not only the connectivity of multimodal public transit networks but also the distribution equity of those systems. The connectivity indices are applied to transit systems in three Tennessee cities at the stop, line, and zone levels. The models and data processes demonstrated in this paper can be used to (i) determine performance of the transit system with no additional data purchase, (ii) assess future service needs, (iii) disseminate transit performance measures for potential future users, and (iv) re-estimate these performance measures to inform network investment decisions.

Further, the transit connectivity measure is used to determine equity by various socio-economic factors using the Gini index. The analysis shows that each studied city exhibits preferences to some groups, but that those groups vary from place to place, but this differential preference can be regarded as space-constrained development of public transport and other involved political constraints. Methods and results presented in this study can provide input to a base framework for state and local DOTs to maintain transit plans, as well for identifying changing service impacts in correlation with changing demographics in order to assess the transportation needs of metropolitan and local communities.

Policy implications derived from this study depend on the ethical paradigm employed by the planning agency. If the purpose of the public transit agency in a particular community is to provide uniform service to all community members, that agency should target a GINI index near zero (where a score near zero indicates perfect equity). However, if the goal is to provide enhanced service to a subset of members (such as captive riders), the system will have a GINI index closer to one—in this case, inequality may not be synonymous with injustice. Similar logic holds when providing a value judgment for equity of distribution by vehicle ownership: if the primary goal of a transit agency is to provide service to captive riders, connective resources should be preferentially distributed to areas with low vehicle ownership. If, however, the primary goal is to ease traffic congestion by reducing trips in single-occupancy vehicles, connective resources should be distributed to areas with high vehicle ownership in order to incentivize participation in public transit. It follows from this discussion that public transit agencies will be able to more effectively deploy their resources if they clearly define the ethical paradigm under which they operate; a sufficientarian stance will necessarily result in a higher inequality score than an egalitarian position. The primary policy implication of this study, then, is that agencies should pair an ethical paradigm with a target GINI index, and should undertake network improvement strategies that reinforce the selected paradigm.

One avenue for further research is the application of this methodology to additional demographic categories, including age, race, and disability. This analysis would allow further identification of vulnerable groups. However, because GTFS data neglects DRT or other Mobility on Demand services, significant modification may be required to analyze the connective resources available to elderly populations or those with disabilities. A second avenue is the analysis of connectivity as it relates to (un)employment percentages; if poor transit connectivity is linked to low employment, such analysis could yield important policy implications for transit authorities and could be used to justify additional investment in transit systems economically. Further, a third avenue may include the development of a toolbox to measure vertical equity levels for groups identified based on the Gini index toolbox employed in this study. Finally, the fourth avenue in future research may incorporate the effect of industrial and warehouse related employment spaces in activity density, which has been used as a proxy variable to capture built environment characteristics.

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Appendix

--Fig. 9(a). here--

--Fig. 9(b). here--

--Fig. 9(c). here--