MEASURING TIME-DEPENDENT ACCESSIBILITY WITH EMERGING MOBILITY OPTIONS: A GENERIC MULTI-MODAL NETWORK MODELING FRAMEWORK

Lindsay Graff
Department of Civil and Environmental Engineering
Carnegie Mellon University
Pittsburgh, PA 15213
lgraff@andrew.cmu.edu

Katherine A. Flanigan, Corresponding Author
Department of Civil and Environmental Engineering
Carnegie Mellon University
Pittsburgh, PA 15213
kaflanig@cmu.edu

Sean Qian
Department of Civil and Environmental Engineering
Heinz College of Information Systems and Public Policy
Carnegie Mellon University
Pittsburgh, PA 15213
seanqian@cmu.edu

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ABSTRACT

As cities aim to improve their holistic transportation networks, emerging mobility options are being integrated at a rapid pace. These modes provide commuters with greater flexibility to construct more convenient trips and reach a larger set of essential service destinations. However, a way to quantify their respective impacts on accessibility across time and space has not yet been introduced in a large-scale network that allows for general cross-modal trips. Moreover, most classical metrics of accessibility in single-mode networks have considered the single trip cost of travel time while also assuming a homogeneous population. To address this challenge of measuring time-dependent accessibility in a multimodal transportation network associated with a diverse set of travel costs, this paper develops a multimodal network modeling framework that accounts for five major factors across all travel modes: day-to-day average travel time, price, reliability represented by day-to-day travel time variability, safety risks, and discomfort. The generalized travel cost of the least-cost path in the multimodal network serves as a metric of accessibility, where the full set of travel modes includes personal vehicle, transportation network companies, car share, public transit, personal bike, bike share, scooter, and walking. The network design was tested with four examples, which showed how shared mobility options have the potential to improve accessibility and provide more reliable travel relative to the status quo of the public transit/walking combination. Using this modeling framework, policymakers can gain insights into spatio-temporal mobility disparities across different populations with different needs.

Keywords: emerging mobility, mobility service, accessibility, micromobility, reliability

INTRODUCTION

The proliferation of shared transportation modes and micromobility infrastructure has changed the way that people travel within urban areas. Commuters are no longer constrained to riding their personal vehicle or using the fixed-schedule public transit network to reach their final destination. Rather, they may use emerging mobility options to construct convenient trips from end-to-end. By harnessing the full extent of the multimodal network, commuters can access a larger set of essential resource destinations, such as workplaces, grocery stores, and hospitals.

As the mobility landscape evolves, several cities including Austin, Boston, and Portland have developed plans to make their multimodal transportation networks more efficient, affordable, reliable, safe, and equitable, all with the goal of improving accessibility to locations that provide goods and services (*1–3*). Ensuring successful implementation requires a way for the cities to measure the ability of different communities to access these points of interest. To address this measurement challenge, this paper develops a multimodal network modeling framework that quantifies time-dependent accessibility in a transportation network. The mobility options included are personal vehicle, transportation network companies (TNC), car share, public transit, personal bike, bike share, scooter, and walk. Planners can use the framework to compare the accessibility of different origin-destination (O-D) pairs across time and space and evaluate where, when, and why mobility is underserved. The proposed method can also be used to determine how changes to the network, such as the addition of micromobility services or a decrease in public transit fare, affect accessibility of points of interest for different neighborhoods.

The stated research goal is related to the objective of the literature in Table 1, which also seeks to measure point-of-interest accessibility for the purpose of planning. However, the analysis in these papers neglects three factors that impact an assessment of accessibility: multimodal travel, a more comprehensive travel cost function, and time-dependency. This research aims to fill that gap by including all relevant transportation options, accounting for multiple travel cost factors, and incorporating travel costs that vary by departure time.

In these papers and others (*11*), accessibility is quantified in different ways. Frequently used accessibility metrics are contour measures, which count the number of "opportunities" (i.e. points of interest) within some travel time contour relative to an origin, and gravity measures, which calculate the sum of opportunities discounted by their travel time relative to an origin. Of note is the fact that these accessibility metrics, among others, require a determination of the shortest path by travel time between O-D pairs. Consequently, this paper chooses to measure accessibility as the cost of the shortest path between an O-D, where cost is defined with respect to travel time, price, reliability, safety, and discomfort.

This work thereby bridges the aforementioned literature on accessibility analysis with the body of research concerned with least-cost multimodal route-finding in large-scale networks. Much of the previous multimodal route-finding research, summarized in Table 2, is focused on the process of efficiently finding optimal paths with respect to the commonly used criteria of travel time and number of transfers. This process-driven research, which mostly centers on improving algorithmic efficiency, is necessary for the development of mobile applications such as Moovit and Citymapper that people use for real-time navigation in an increasingly multimodal world (*12*). Unlike this type of routing research, this paper does not concentrate on the algorithmic or runtime efficiency components of pathfinding, nor does it outline a data-gathering procedure for finding a multimodal route in real-time. Instead, the research objective is to design a comprehensive multimodal network including all possible mobility options for the purpose of examining possible path

TABLE 1: Literature Review: Accessibility Evaluation

Study	Objective	Population Considered	Accessibility Metric(s)	Travel Modes	Travel Cost	Time-dependent Analysis
Tribby and Zandbergen (*4*)	measure and compare accessibility by way of PT	–	TT of SP	PT, walk	TT	✓
Djurhuus et al. (*5*)	determine individual-based accessibility areas by way of PT	–	total accessible area	PT, walk, personal bike	TT	✓
El-Geneidy et al. (*6*)	measure and compare accessibility by way of PT	socially disadvantaged	cumulative opportunities	PT, walk	TT, price	✓
Chen et al. (*7*)	measure and compare accessibility by way of PT	–	1. gravity metric 2. TT of SP, weighted by destination importance	PT, walk	TT	–
Järv et al. (*8*)	measure and compare accessibility to services by time of day	–	TT of SP	PT, walk	TT	✓
Carpentieri et al. (*9*)	measure accessibility of elderly people to healthcare services	elderly	gravity metric	PT, walk	TT	–
Yu et al. (*10*)	evaluate multimodal accessibility with resepct to TT and price budgets and under TT uncertainty	–	cumulative opportunities	TNC, PT, walk	TT, price, reliability	–
This paper	measure and compare accessibility between heterogeneous regions in a time-dependent multimodal network	Population characterized by time, location and socio-demo	total cost of SP	personal vehicle, TNC, car share, PT, personal bike, bike share, scooter, walk	TT, price, reliability, risk, discomfort	✓

Notes: "TNC" = transportation network company; "PT" = public transit; "TT" = travel time; "SP" = shortest path; "✓" indicates that time-dependent analysis is possible with the proposed method; "–" indicates that time-dependent analysis is not possible

TABLE 2: Literature Review: Multimodal Route-finding

Study	Use Case	Travel Cost	Included Travel Modes		Case Study	
			Shared Micromobility	On-demand Service	Network Size	Data Type
Delling et al. (*13*)	RTRP	TT	–	–	>1 million nodes	real
Zhang et al. (*14*)	RTRP	TT + price + effort + discomfort	–	–	>10,000 nodes	real
Delling et al. (*15*)	RTRP	TT, price, inconvenience	✓	✓	>250,000 nodes	real
Hrnčíř and Jakob (*16*)	RTRP	TT	✓	✓	>100,000 nodes	real
Dibbelt et al. (*17*)	RTRP	TT	–	–	>1 million nodes	real
Georgakis et al. (*18*)	RTRP	TT	✓	✓	N/A	N/A
Huang et al. (*19*)	RTRP	TT	–	✓	>6,500 nodes	real
This paper	accessibility analysis	TT + price + reliability + risk + discomfort	✓	✓	>7,500 nodes	real

Notes:
"RTRP" = real time route planning; "TT" = travel time; shared micromobility" includes bike share and scooter; "on-demand service" includes TNC and demand-responsive transit; "generalized travel cost" is a travel impedance that includes additional elements beyond just travel TT; "✓" indicates inclusion by the study; "–" indicates not included by the study; "Network Size" does not include time event nodes from the time-expanded public transit network model

choices for individual travelers. With this network model, transportation planners can quantify the accessibility of relevant points of interest for different communities to gain insight into where network improvements can be made. This paper uses elements of the literature of Table 2 in designing a connected multimodal network model that permits a determination of the shortest path between points.

The rest of this paper is structured as follows. First, the design of the multimodal network, assignment of travel costs, and process for measuring accessibility between an O-D pair is presented. Second, the proposed method is demonstrated using a subset of the transportation network in Pittsburgh, PA, and the results of the study are discussed. The final section highlights key conclusions and identifies opportunities for future work.

METHODOLOGY

The process of measuring accessibility in a regional multimodal network involves three stages: designing the multimodal network, defining an edge cost function, and finding the least-cost path between selected O-D pairs based on characteristics of travelers. The first step to constructing the

TABLE 3: List of Notation

G_m	graph associated with travel mode m
N_m	set of graph nodes associated with G_m
A_m	set of graph edges associated with G_m
N_{dr}	set of road intersection nodes in the driving network
A_{dr}	set of road segment edges in the driving network
N_{pk}	set of parking nodes
$A_{pk,cnx}$	set of edges that connect parking nodes to their nearest neighbor node in the driving network
N_b	set of road intersection nodes in the bikeable network
A_b	set of road segment edges in the bikeable network
N_{ps}	set of public transit physical stop nodes
N_{rt}	set of public transit virtual route nodes
A_{board}	set of edges from physical stop nodes to associated virtual route nodes, which represent the process of waiting and boarding
A_{alight}	set of edges from virtual route nodes to associated physical stop nodes, which represent the process of alighting
A_{rt}	set of edges between virtual route nodes
N_{bsd}	set of bike share depot nodes
$A_{bsd,cnx}$	set of edges that connect bike share depot nodes to their nearest neighbor node in the bikeable network
A_{bsd}	set of precomputed edges that connect bike share depot nodes
N_{csd}	set of car share depot nodes
$A_{csd,cnx}$	set of edges that connect car share depot nodes to their nearest neighbor node in the driving network
A_{tx}	set of transfer edges
N_{OD}	set of origin nodes and destination nodes
$A_{OD,cnx}$	set of edges that connect the origin and destination nodes to the component networks

multimodal network is to model each single-mode transportation network as a graph consisting of road intersection nodes and road edges. These graphs are then connected to each other by transfer edges at relevant nodes where transfers are likely to take place, which results in a single multimodal graph, or "supernetwork" (*20, 21*). Once the network topology is determined, a time-varying travel cost is assigned to each edge. In this work, the travel cost is given by the weighted sum of travel time, price, reliability, and risk. A time-dependent shortest path algorithm is subsequently used to find the least-cost path between selected O-D pairs for different departure times. Table 3 specifies the notation used in this paper.

Multimodal Network Design

This work considers an exhaustive list of possible travel modes: personal vehicle (PV), transportation network company (TNC), car share (CS), public transit (PT), personal bike (PB), bike share (BS), scooter (S), and walking (W). The component network for each travel mode m is modeled separately and represented by a graph $G_m = (N_m, A_m)$. Whereas some modes (e.g., TNCs) allow

travelers to hail a ride or exit at any point in that mode's network, others such as public transit and bike share require that commuters only move between fixed points. The supernetwork consists of these component networks joined together by transfer edges. Origin and destination nodes are joined to certain points in the component networks by connector edges. It is important to note that this network only models outbound trips where a person commutes from their neighborhood to a point of interest. This distinction is necessary because modeling the inbound trip would require the reversal of some transfer edges and connection edges within the personal vehicle and car share component networks.

Personal Vehicle

The personal vehicle network $G_{PV} = (N_{dr}, N_{pk}, A_{dr}, A_{pk,cnx})$ consists of the typical street map used by drivers. Road intersections comprise the graph's core set of intersection nodes, which are connected by road segment edges. A parking connector edge joins each parking node to its nearest nearest neighbor street intersection node in the driving network. The directional connector edge goes from the street intersection node to the parking node since this network model only considers the outbound trip; once a person parks their car, they do not use their personal vehicle again on the outbound trip.

TNCs

The TNC network $G_{TNC} = (N_{dr}, A_{dr})$ is created by duplicating the personal vehicle network and removing parking nodes and their connector edges. Riders in the TNC network can choose their point of entry and exit at their convenience.

Car Share

Commuters using a car share rental vehicle, which they must pick up at a depot, use the personal vehicle network to drive and park their shared vehicle. The car share component network can be thus modeled as $G_{CS} = (N_{dr}, N_{pk}, N_{csd}, A_{dr}, A_{pk,cnx}, N_{csd,cnx}, A_{csd,cnx})$. In this model, N_{csd} specifies the set of all car share depot locations and $A_{csd,cnx}$ denotes the set of connector edges that join the each depot to its nearest neighbor node in the rest of the network. Modeling only the outbound trip requires that these directional edges go from the depot to the street intersection node; after a commuter rents a vehicle, they do not return the vehicle on the same outbound trip (the vehicle is returned on the inbound trip).

Public Transit

A time-dependent network $G_{PT} = (N_{ps}, N_{rt}, A_{board}, A_{alight}, A_{rt})$ is used to model the public transit network (*22*). This model contains two types of nodes: physical stop nodes N_{ps} and route nodes N_{rt}. Physical stop nodes represent actual locations in the network where travelers board or alight a bus. Since more than one bus route can pass through a physical stop, each stop is also linked to one or more route nodes. The edge from a stop node to a route node represents the cost of waiting and boarding, whereas the edge from a route node to a stop node represents the cost of alighting. Hence, it is possible to switch routes at one physical stop by using an alighting edge tied to one route node and a boarding edge tied to a different route node. The graph also consists of route traversal edges in the set A_{rt} which connect route nodes, where the weight of each route edge corresponds to the cost of traveling along that particular bus segment. The time-dependent model of public transit was selected over the time-expanded model for its smaller size and easier

integration with other component graphs.

Personal Bike

The personal bike network $G_{PB} = (N_b, A_b)$ includes road edges that are considered bikeable according to the OSMnx package in Python (*23*). Per the OSMnx package definition, a road is considered bikeable unless it is a highway, private road, or a street specifically marked for pedestrians.

Bike Share

The original bike share network $G_{BS} = (N_b, N_{bsd}, A_b, A_{bsd_c nx})$ is formed by duplicating the personal bike network and then adding bike share depot nodes and bike share connector edges. The depot nodes represent the locations where travelers can pick up or drop off a shared bicycle. A bidirectional bike share connector edge joins each depot node to its nearest neighbor intersection node in the bike share network, similar to how parking and car share depot connector edges are implemented.

Since a traveler using a shared bike must pick up and drop off the bicycle at a depot, it is possible to consolidate the bike share network into a set of depot nodes and depot edges. Shortcut bidirectional depot edges connect depot nodes directly to each other, where a shortcut edge between nodes represents the least-cost path between them. The precomputed network $G_{BS,pre} = (N_{bsd}, A_{bsd})$ is useful for simplifying the graph and expediting processing time when evaluating shortest paths in the full multimodal network.

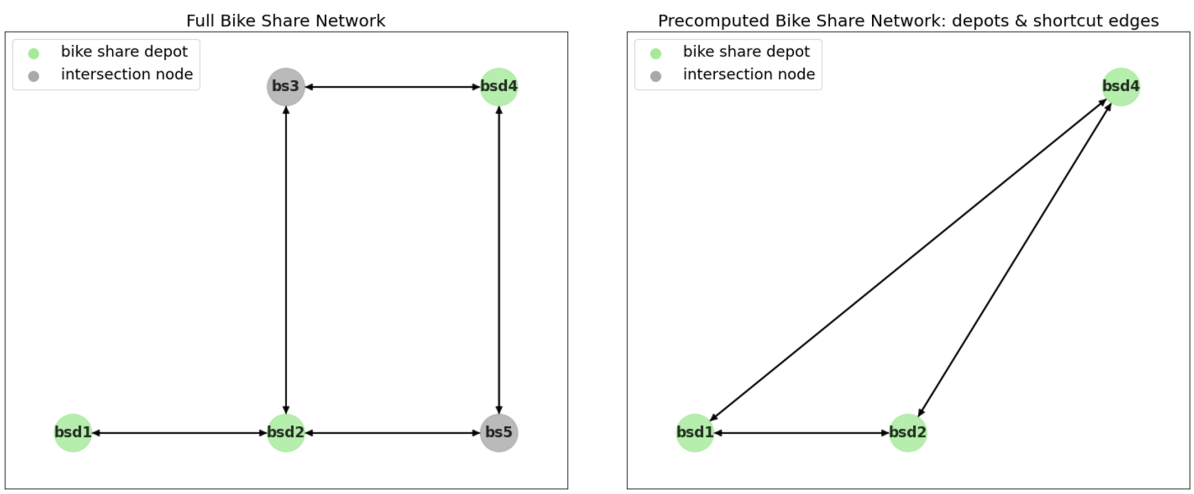


FIGURE 1: An example showing how precomputing shortcut bike share edges can reduce the size of the network.

Scooter

The scooter network $G_S = (N_b, A_b)$ is modeled as a duplicate of the personal bike network. The inherent assumption is that scooters may use the same roads as a bicycles. Explicitly modeling the location of a scooter pickup node is not possible since riders may leave scooters in any valid parking spot in the network. Given that this network model is being used for planning purposes as opposed to real-time navigation, it is also not necessary to identify exact scooter locations. Instead, data can be used to estimate the average distance that a person must walk in order to pick up the

nearest scooter. This estimation process, which is embedded in the procedure for building transfer edges, is explained in section 3.1.9

Walk

The full walking network is not explicitly modeled in this design. Rather, only certain relevant walking segments are included. The relevant walking segments pertain to the following scenarios: transfers between two component networks, connections from the origin to the component networks, and connections from the component networks to the destination. For example, a transfer between a bike share depot and a public transit physical stop is modeled as a single walking segment whose approximate distance is equivalent to the Haversine distance between the depot and stop node. This modeling decision removes the need to include the full walking network, which simplifies the design.

Transfer Edges

After modeling each component network, transfer edges are created to connect component networks to each other. Transfer edges that form the set A_{tx} are directional and assumed to be traversed by walking. Locations in a component network where a mode change may take place are called switch points, following the approach of (*24*). If the switch point is at a predetermined location (e.g bus stop, bike share depot, parking node), it is denoted a "fixed pickup" or "fixed drop-off" node; if the switch point changes depending on the commuter's needs (e.g., TNC pickup point), it is considered a "flexible pickup" or "flexible drop-off" node. Each transfer link is constructed by joining a switch point in one component network to a switch point in another. A multimodal graph with transfer edges is depicted in Figure 2, which demonstrates a small example network that includes the bike share, public transit, and TNC modes. The component networks in this figure are slightly offset for visualization purposes, since they physically overlap.

Building transfers efficiently requires the specification of constraints on allowable switches between travel modes. Figure 3 enumerates the plausible mode changes, where the arrows indicate the direction of the change. This list of allowable changes between modes is based on practical considerations. One such assumption is that travelers using a personal or car share vehicle can switch from the driving mode to another mode only after dropping their vehicle in a parking zone. In addition, changing modes from personal bike to public transit is enabled by the presence of a bike rack on a bus. It is also assumed that intermediate bike parking is not available and bike racks do not exist on other vehicles, which implies that travelers who ride their personal bike on any part of a path can use only a combination of the personal bike, public transit, and walking networks. In addition, any modal transfer can be associated with a specific generalized cost that influence the optimal path finding, e.g., convenience, cost, fare discount or discomfort. This is achieved by imposing node-based generalized cost to associate any specific edge-to-edge movement. The cost can be set arbitrarily small to imply seamless connection, negative to imply fare discount offered to use two specific modes sequentially, or arbitrarily large to imply prohibition between any two modes.

An additional assumption in this network design is that travelers are willing to walk a distance less than or equal to W when transferring modes. The implication is that for every fixed drop-off node in any component network, there exists a "walking catchment zone" (WCZ) which contains all surrounding nodes within a Haversine distance of W. Though this approximation underestimates true network walking distance, it is assumed to closely represent actual distance

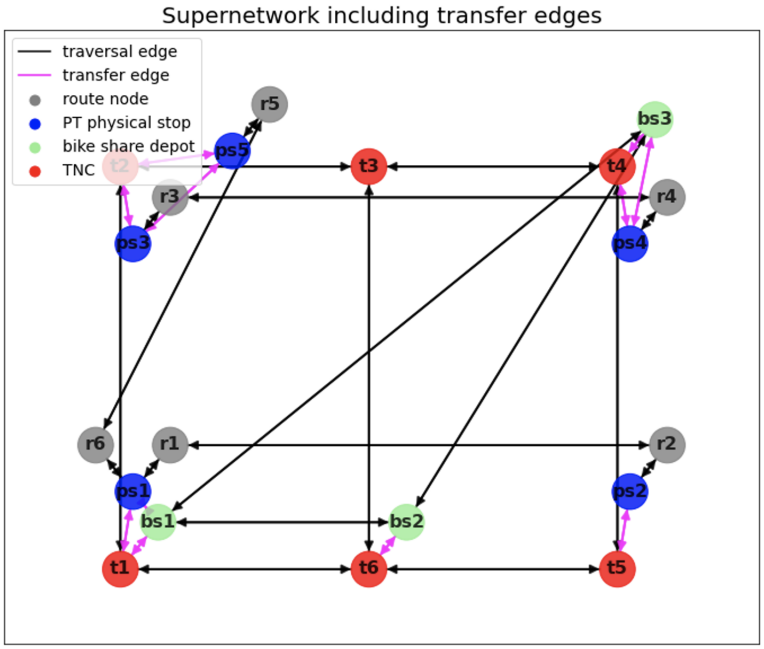


FIGURE 2: Example supernetwork with transfer edges for bike share, public transit, and TNC networks.

Mode 1		Mode 2
Public Transit	⟷	Public Transit
Public Transit	⟷	Bike Share
Public Transit	⟷	TNC
Public Transit	⟷	Personal Bike
Public Transit	⟷	Scooter
Public Transit	→	Car Share
TNC	⟷	Bike Share
TNC	→	Car Share
Personal Vehicle	→	Public Transit
Personal Vehicle	→	TNC
Personal Vehicle	→	Bike Share
Personal Vehicle	→	Scooter
Bike Share	⟷	Scooter
Bike Share	→	Car Share
Scooter	→	Car Share
Walk	⟷	*Any Mode*

FIGURE 3: Allowable Mode Changes

due to the presence of walking shortcuts. However, it is not necessary to build a WCZ for flexible pickup/drop-off networks. The reason is that, when given a choice of where to be dropped off in a flexible network, travelers would logically always choose the drop-off node is that nearest the next pickup node they wish to use. Thus, if the transfer is allowed, a transfer edge is drawn from a fixed drop-off node to the nearest node in flexible pickup network and vice versa for a fixed pickup node.

In previous research (*13*)(*14*), transfer edges are created by joining switch points in one component graph to their nearest neighbor in the reference walking network. Constraints relating to the mode sequence are then enforced at runtime by the use of a specific label-constrained algorithm or by the inclusion of a only a subset of component graphs. The approach in this paper, which is similar to (*24*), is different in the sense that transfer links embed mode sequence constraints. This eliminates the need to use a label constrained shortest path algorithm.

Origin and Destination Connectors

Transportation planning analysis is typically conducted on an aggregated geographic level, where the geographic entity is selected to represent the travel patterns of many people within the entity (*25*). Common geographic units include traffic analysis zones and census block groups. The proposed network model uses the centroids of the geographic unit as both origins and destinations so that accessibility between regions can be measured. The set of origin and destination nodes is called by N_{OD}. Each origin is connected to nearby pickup nodes by origin connector edges and each drop-off node is connected to nearby drop-off nodes by destination connector edges. An O-D pair and its associated connector edges, denoted by $A_{OD,cnx}$, is added to the network on the fly at the time of evaluation to minimize network size.

The procedure to build O-D connector edges is similar to the process of creating transfer edges. The idea is that a traveler can transfer from the origin to any component graph that has a fixed pickup node within the origin's WCZ, and vice versa for fixed drop-off nodes within a destination's WCZ. However, if there is no fixed pickup node within an origin's WCZ for a specific mode, an edge is instead created from the origin to the nearest fixed pickup node in the mode's component network. This modeling choice reflects the reality of a commuter's decision-making process, as they are they are more likely to walk a longer distance on the first leg of their journey rather than at an intermediate stage. The same exception is made if all fixed drop-off nodes of a specific mode type exist outside a destination's WCZ. An origin connector edge also joins the origin to its nearest neighbor in flexible pickup networks, and a destination connector edges joins the destination to its nearest neighbor in flexible drop-off networks.

Supernetwork

The multimodal graph is defined as the union of all component networks, transfer edges, O-D nodes, and O-D connector edges:

$$G_{MM} = G_{PV} \bigcup G_{TNC} \bigcup G_{CS} \bigcup G_{PT} \bigcup G_{PB} \bigcup G_{BS} \bigcup G_{S} \bigcup A_{tx} \bigcup N_{OD} \bigcup A_{OD,cnx} \tag{1}$$

Cost Assignment

Transportation planners can use this network model to measure accessibility between points by departure time. This paper defines accessibility from an origin to a destination as the total cost of the least-cost path between them in a multimodal network. Finding the least-cost path requires

a cost determination for each edge and node in the graph, followed by the process of running a shortest path algorithm.

Generalized Cost Function

One way that the proposed method distinguishes itself from previous research is by defining the edge cost function as a combination of five time-dependent factors: price, average travel time, reliability, risk, and discomfort. The total cost C of an edge e is defined as a linear combination of the five individual attributes as a function of departure time t, given by equation 2.

$$C_e(t) = \beta_p \cdot p_e(t) + \beta_{TT} \cdot TT_e(t) + \beta_r \cdot r_e(t) + \beta_k \cdot k_e(t) + \beta_D \cdot D_e(t) \tag{2}$$

where p is the price, TT is the average travel time, r is the reliability, k is the risk, and D is the perceived discomfort value. All cost factors are defined with respect to edge e and departure time t. Reliability is measured by the edge's 95th percentile travel time, following common practice in the transportation engineering field (*26*). The edge's risk k_e is quantified by its unitless risk index x_e multiplied by its average travel time TT_e, where the risk index considers the road segment's vehicle crash rate for vehicle networks or the road segment's availability of micromobility infrastructure for micromobility networks. The discomfort attribute of an edge represents the level of physical exertion required for its traversal. This model assumes that an edge's discomfort attribute is zero for all inactive commuting modes, which includes all modes that use vehicle travel. Active modes, which include biking, walking, and scooter-riding according to the Department the Energy's Alternative Fuels Data Center (*27*), are associated with some degree of physical difficulty. In this work, the discomfort value of an edge D_e is quantified by a discomfort weight parameter d multiplied by the edge's average travel time TT_e. The benefit of defining reliability, risk, and discomfort in terms of travel time is that the attributes are on the same scale such that no single factor completely dominates the cost function.

The β parameters can be interpreted as the dollar value that a person assigns to a single unit of the cost factor. The parameter β_p thus takes on the unitless value of 1, while β_p has units of dollars per minute and is representative of a person's value of time. When conducting analysis, the β parameters can be adjusted based on the population group under consideration or the goals of the transportation planner. For example, a planner interested in bike safety may choose to give higher weight to β_k. A planner may also choose to assign a higher value of time β_{TT} when evaluating path options during commuting hours vs. off-peak hours.

Regarding time dependency, inactive modes are assumed to be unaffected by traffic flow such that all associated edge costs are constant with time. The travel time and reliability of the traversal edges of the personal vehicle, TNC, and car share modes vary with time in accordance with traffic flow, while price is constant. For TNC and car share edges, however, price also changes with time because their price is correlated with usage time. The travel time and reliability of public transit edges are time-dependent as a result of both the fixed schedule and traffic conditions. The risk index and discomfort weight associated with an edge are assumed to remain constant regardless of departure time.

Transfer Edge Costs

The cost vector of a transfer edge consists of the cost attributes that are associated with the shortest walking path between the two nodes that define the edge, in addition to a dollar-valued inconve-

nience cost that is associated with the act of transferring. The distance of the shortest path can be estimated as the Haversine distance between the two nodes, an approximation that simplifies the transfer edge cost calculation. The price attribute of a transfer edge is considered to be $0, which is consistent with the price associated with a walking path, unless parking or other fixed costs are embedded into the edge.

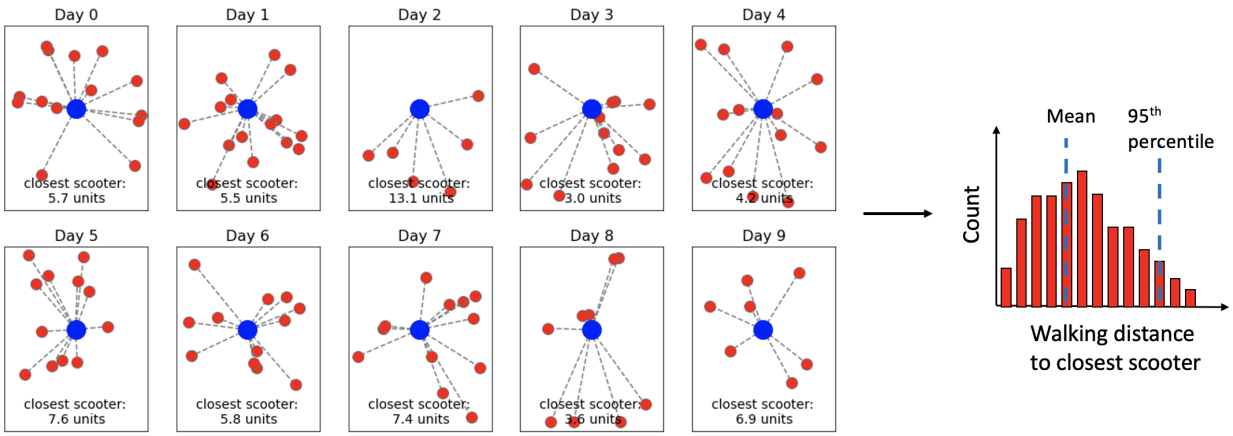


FIGURE 4: An example of 10 historical daily scooter observations (red) for a given time interval shown relative to a specified fixed node (blue). The average and 95th percentile distance to the nearest scooter are used to assign scooter transfer edge costs.

For directional transfer edges that connect fixed drop-off nodes to the nearest intersection node in the flexible scooter network, the time-dependent cost vector is estimated based on historical observations of physical scooter locations. If given the actual location data of all scooters by date and departure time, one can find the distance between any fixed drop-off node and its nearest physical scooter for the specified date and departure time pair. Repeating this process for n days results in a distribution of the distance, which can be converted to walking travel time, from each fixed node to its nearest scooter. From this distribution, the average and 95th percentile walking time from a fixed node to its nearest scooter can be derived. This procedure, which is depicted with an example in Figure 4, can also be used to model the average and 95th percentile waiting time for a TNC vehicle.

Node Costs

In addition to edge costs, movement-based node costs are added to the model. These node costs represent a penalty on moving from one link to another via a particular node. For this network model, movement-based node costs can be used to prevent or discourage certain behavior, such as the usage of two consecutive transfer edges. Without node costs, the least-cost route may consist of several connected transfer edges that effectively create a longer transfer edge whose length exceeds the parameter W defined in the Transfer Edges section. This situation could arise if β_{TT} is low. Since transfer edges are traversed by walking, they have a price of zero and minimal risk and discomfort costs; hence they are desirable from a cost standpoint if value of time is low.

Accessibility Analysis

Once costs are assigned to the multimodal network, it can be used to evaluate accessibility on an O-D level in addition to an origin level or a destination level. On the O-D level, accessibility is defined as the cost of the least-cost path between two points. This use-case will be explored in the next section. This framework also enables an assessment of origin-level accessibility, where the quantity of essential service destinations reachable by a given origin within some cost threshold can be compared. Destination-based accessibility can be evaluated in a similar manner; policymakers can determine the number of origins able to reach a particular destination to better understand its value to the network. The time-dependent least-cost path necessary for this analysis can be found with the decreasing order of time algorithm presented in (*28*).

CASE STUDY

The proposed methodology is demonstrated on a group of demographically-different neighborhoods in Pittsburgh, PA. In all test cases, the personal vehicle network is excluded from the supernetwork since the population of interest is assumed to not have access to private vehicles. The final supernetwork, inclusive of all traversal, transfer, and O-D connector edges, has 7,924 nodes and 53,988 edges. To test the multimodal route-finding capability, census block group centroids are used as origin and destination nodes. A two-hour departure window divided into thirteen time intervals is considered, and the time-dependent algorithm is provided by open-source code on Github [1] detailed in (*29*).

Network Settings and Data

The area's driving and biking networks are extracted from the Python package OSMnx, which downloads geospatial data from OpenStreetMap and then simplifies the network topology (*23*). Locations of bike share depots, bike lanes, parking meters, and parking rates are obtained from the Western Pennsylvania Regional Data Center (*30*). For simplicity, the parking nodes are consolidated into one representative node per parking zone, represented by the average location of a parking meter within a zone. The cost of parking is calculated as the product of the hourly parking rate and the number of parking hours, which is assumed to be eight hours in accordance with a full work day. Public transit stop locations and route information are provided by the General Transit Feed Specification (GTFS), and the locations of Zipcar (*31*) depots are found by querying Google My Maps (*32*) and downloading the coordinate pairs returned. While this method for extracting car share locations is not entirely accurate, it serves the purpose for testing the model. In the Pittsburgh region, Zipcar runs the car sharing service, POGOH (*33*) operates the bike share system, Spin (*34*) manages the scooter fleet, and Pittsburgh Regional Transit (*35*) acts as the public transit agency.

Assigning cost attributes to the edges requires the specification of several parameters, which are listed in Table 4. Prices for a Zipcar car share, POGOH bike share, Spin scooter, and Port Authority bus ride are obtained from various company or agency websites. Travel speed parameters for bicycles, personal vehicle operating costs, TNC prices, and waiting time for TNC vehicles are based on previous research (*36–40*), with presumed equivalence between scooter and bike speeds. The traversal time between bus stops and average headway between bus trips are both based on GTFS schedule data, and the average waiting for a bus, regardless of the commuter's arrival time at the stop, is assumed to be half of the bus headway time per convention (*41*). To

[1] https://github.com/psychogeekir/MAC-POSTS

calculate the risk index, the factors considered for the micromobility networks are road type and bike lane presence, while the single factor considered for the driving networks is vehicle crash rate. Movement-based node costs are also added to prevent a route that uses two consecutive transfer edges. Finally, the walking catchment zone parameter W is set at 0.5 miles to prevent transfer or O-D connection edge lengths greater than this value.

Data that was not available for this case study is estimated. The unavailable information includes actual historical travel time data for any of the vehicle networks, as well as historical scooter observations. For average traversal time between transit stops, GTFS schedule data is used instead. The average travel time for edges in the driving networks is assumed to be the product of its speed limit, length, and a travel multiplier used to represent the ebb and flow of morning traffic. This multiplier function is generated as a bell-shaped curve with a value of 1 at the start and end of the departure window and a value of 1.5 in the middle of the window. In the time-dependent vehicle networks, each edge's reliability attribute, which is represented by its 95th percentile travel time, is approximated as its average travel time multiplied by a factor of 1.5. Edges traversed by active modes are assumed to have time-invariant travel times such that their reliability attributes equate to their average travel times. Finally, data pertaining to historical scooter locations is generated artificially for 30 days for each time interval by distributing 100 scooters throughout the region in a random uniform way.

For the subsequent examples, the β parameters are defined as $\beta_p = 1$, $\beta_{TT} = \$10$/minute, $\beta_k = \$1$/minute, and $\beta_d = \$0.5$/minute. The value of β_r is adjusted in the fourth case to show how this parameter affects the selection of the least-cost route.

Results

To show the flexibility of the proposed framework, the example for this case study compares the accessibility between the same O-D pair for four separate cases. The first three cases (Case 1, Case 2, and Case 3) use $\beta_r = \$0.75$/minute and the other parameters detailed above. In Case 1, all modes of travel are available, whereas the scooter network is removed in Case 2, and both the scooter and bike share networks are removed in Case 3. The fourth case (Case 4) models the situation where the traveler places a higher value on reliability, indicated by $\beta_r = \$5$/minute, which could be representative of a commuter's mindset en route to work. All modes of travel are permitted in Case 4. To further test the importance of reliability to the commuter, the reliability cost attribute of a public transit boarding edge is increased from $1.5 \cdot TT$ to $2 \cdot TT$. All examples use the same O-D pair, where the origin and destination are the centroids of block groups with FIPS codes 420035623001 and 420031402001, respectively. Comparisons of path costs are made in relative terms since absolute costs do not have physical significance.

The resulting least-cost paths are shown in Figure 5. When all modes are available, the traveler characterized by this set of β parameters has an optimal route that begins the trip with a scooter and finishes with a bike share. The transfer to the bike share network in the middle of the trip can be rationalized by the bike share's cheaper price; the price of a bike share edge is \$0.066 per minute whereas the scooter cost is \$0.39 per minute. This optimal route shows the potential of shared micromobility modes to reduce overall travel costs and improve accessibility for those capable of using active modes of travel.

From Case 1 to Case 2, the generalized travel cost increases by 11.4% as commuters switch from a scooter on the first leg of their trip to public transit. Still, the path includes a bike share for the final segment. The fact that the bike share network is used at the end of the trip in both cases

TABLE 4: Specification of parameters used for the Pittsburgh case study

Travel Mode	Price	Travel Time	Waiting Time	Risk Index	Discomfort Weight
Personal Vehicle	\$0.64/mile	(speed limit) · (road length)	0 min	1 + α · (crashes/meter)	0
TNC	\$2.55/ride + \$1.75/mile + \$0.35/min	(speed limit) · (road length)	7 min	1 + α · (crashes/meter)	0
Car Share	\$11/60 min	(speed limit) · (road length)	0 min	1 + α · (crashes/meter)	0
Public Transit	\$2.75/ride	GTFS traversal time	(GTFS headway time) / 2	1	0
Personal Bike	\$0.00/ride	(15 km/hr) · (road length)	0 min	1 if bike lane or bike only, else 100,000 if major road, else 1.2	0.30
Bike Share	\$20/300 min	(15 km/hr) · (road length)	0 min	1 if bike lane or bike only, else 100,000 if major road, else 1.2	0.30
Scooter	\$1/ride + \$0.39/min	(15 km/hr) · (road length)	walk time to nearest scooter	1 if bike lane or bike only, else 100000 if major road, else 1.2	0.10
Walk	\$0.00/min	(1.3 m/s) · (road length)	0 min	1	0.10

Note: α is a risk parameter that weights the value of the vehicle crash rate. The parameter $\alpha = 5$ was selected for scaling purposes.

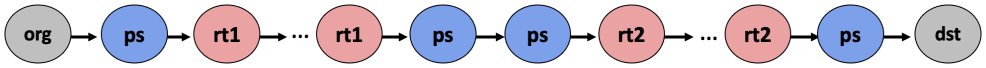
indicates that the destination is in close proximity to a depot, which helps improve the destination's accessibility at least with respect to this particular origin.

In Case 3, the scooter and bike share networks are removed to model the travel preferences of travelers for whom active modes are not a feasible alternative, such as the elderly or disabled. From Case 1 to Case 3, the generalized travel cost increases by 68.6% as these travelers take their full trip using public transit. The least-cost route requires a transfer, which leads to a sizeable increase in travel cost likely due to a waiting penalty. A public transit agency aiming to improve accessibility between this O-D pair specifically for this population group may consider increasing the frequency of the bus line used for the second leg of the trip.

Case 4 results in a route exclusively in the TNC network, even when all other modes are available. Although micromobility modes are reliable in the sense that the 95th percentile travel time for each edge is equivalent to the edge's average travel time, it still takes longer to commute by active modes as opposed to a private ride share vehicle in the driving network. This means that it could still be the case that the 95th percentile travel time in a driving network is lower than the average travel time in an active mode network. For a commuter who is highly sensitive to the 95th percentile travel time between this O-D pair, the TNC network provides an optimal route choice. It

(a) Case 1: Least-cost route between O-D pair with personal vehicle network excluded.

(b) Case 2: Least-cost route between O-D pair with personal vehicle and scooter networks excluded.



(c) Case 3: Least-cost route between O-D pair with personal vehicle, scooter, and bike share networks excluded.

(d) Case 4: Least-cost route between O-D pair with β_r = \$5/minute and personal vehicle network excluded.

FIGURE 5: Four different least-cost routes are found between the same O-D pair depending on the presence of the micromobility networks and the value of the β_r parameter. "org" = origin, "s" = scooter node, "bs" = bike share depot node, "ps" = physical stop node, "rt" = route node (the number refers, "tnc" = TNC node

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is worthwhile to note that the TNC option provides a reliable route due to the assumed reasonable pickup waiting time of 7 minutes. If it were the case that the region had limited TNC drivers and a longer wait time or a high surge price, the optimal path could change.

CONCLUSION

In this paper, a modeling framework to evaluate time-dependent accessibility in a multimodal network was proposed. This framework builds upon previous literature in several ways. First, it incorporates all relevant mobility options including personal vehicle, TNC, car share, public transit, personal bike, bike share, scooter, and walking. In addition, it defines a generalized travel cost function that accounts for average travel time, price, reliability, risk, and discomfort, as well as a movement-based node cost that can impose additional (dis)incentives for any multimodal trip. Since each factor is assigned a weight that represents its value to the traveler, these weights can be tailored to different population groups. This framework can be used by transportation planners as they evaluate where to add and improve mobility services with the goal of creating a more accessible and equitable mobility system. Planners can also use this model to examine how any change to mobility services can potentially impact individual travelers with different starting points, departure times, or socio-demographics.

To demonstrate this model in real-world large-scale network, four scenarios are explored in the Pittsburgh metropolitan network. The results exhibit the potential of micromobility to improve access between a specific O-D pair by leading to a sizable reduction in generalized travel cost relative to the baseline public transit and walking case. The case study also highlights the ability to

account for different population groups via parameter adjustment, which points to an opportunity for future work in sensitivity analysis of the various parameters and cost functions.

Additional future work includes more careful consideration of the discomfort and risk index definitions, as well as the use of actual historical data to more accurately determine the travel time and reliability attributes. Another application of this modeling framework is estimation of the pattern of network usage for each mode and facility in high granularity. This can be accomplished by aggregating least-cost paths for all individuals across multiple O-D pairs to find commonly-used nodes and links. Such an assessment could inform a decision on when, where, and how to improve mobility services.

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AUTHOR CONTRIBUTION STATEMENT

LG: study design, literature review, data processing, data analysis, interpretation of results, manuscript preparation. KF: study conception and design, interpretation of results, manuscript preparation. SQ: study conception and design, data collection, interpretation of results, manuscript preparation.

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