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Impacts of Transportation Network Companies on Urban Congestion in a Medium-Sized City

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IMPACTS OF TRANSPORTATION NETWORK COMPANIES ON URBAN CONGESTION IN A MEDIUM-SIZED CITY

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ABSTRACT

The rise of ride-hailing and on-demand transportation services offered by Transportation Network Companies (TNCs) (such as Uber and Lyft) has been one of the key factors contributing to the growth of shared mobility services in recent years. The presence of contradictory findings on the impacts of TNCs necessitates the undertaking of an investigation into the shifts in mode choice that occur in the context of TNC services and their impacts on urban congestion. As a result of difficulties in gathering TNCs field data, it is still not possible to fully assess the impact of these services on urban congestion. Moreover, studies that investigated how TNC services affect the operational efficiency of the transportation system focused primarily on large-sized cities and the impacts of such services in medium-sized cities are still not well understood. In an effort to address such gaps, the purpose of this study is to demonstrate the feasibility of using simulation modeling to assess the impact of TNC services on urban congestion in medium-sized cities, utilizing Birmingham, AL as a case study.

The study commenced by conducting a comprehensive literature review and examining research case studies to identify simulation platforms suitable for modeling shared mobility. This process helped to identify the Multi-Agent Transport Simulation (MATSim) as the most viable and established platform for simulating TNCs services. The study then utilized the MATSim platform to evaluate the impact of various types of TNC services on urban congestion. Significant efforts were placed in the development of

a comprehensive model of the Birmingham area that realistically represented trips of Birmingham travelers using a variety of transportation modes including private automobile, transit, walking, and on-demand shared modes (Uber and Lyft). In order to model the latter, a survey of Uber drivers was conducted and used in combination with population statistics from census data to generate realistic Uber rides for the Birmingham agent-based simulation. In this study, two categories of ride requests from a TNC were simulated, namely individual ride requests and ride-pooling requests. Two types of ride-pooling services were considered in the simulation, namely door-to-door (d2d) and stop-based (sB) services.

Key findings of the study revealed that the addition of TNC vehicles to the network resulted in a significant increase in Vehicle Kilometer Traveled (VKT) for TNCs' individual ride requests and a reduction in VKT for both ride-pooling categories (d2d and sB). Moreover, the study allowed to identify the optimal TNC fleet size for the Birmingham region, which was found to be double the size under the TNC individual ride option, compared to the ride-pooling service options.

Given the limited existing research on the effects of TNCs on traffic congestion in medium-sized cities, the findings of this study hold substantial value in terms of bridging the gap between the introduction of TNCs and their impact on traffic operations in a medium-sized city. This research work provides valuable contributions to the current body of knowledge related to multimodal modeling using an open-source large-scale agent-based transportation simulation platform. As such, the findings and results of this study are anticipated to be beneficial for researchers and practitioners in their planning efforts of including TNC services into their planning models. The findings of the case studies reported can also assist transportation decision makers, urban planners, and TNC providers in their efforts to optimize their operations and serve the needs of the traveling public better in the future.

Keywords: Demand Responsive Transit (DRT), MATSim, On-demand ridesourcing, Ride-pooling, Ride-sharing, Transportation Network Companies (TNCs), Uber, Lyft.

DEDICATION

I dedicate this dissertation to both my beloved father, Shakir, and mother, Sajida, who both had an immense impact on my life, and both passed away during the course of my doctoral program. Your unwavering love, support, and encouragement have motivated me to begin to pursue the dreams and aspirations I have always had. I would also like to dedicate this dissertation to my siblings, who have provided me with encouragement and support throughout my academic journey.

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LIST OF ABBREVIATIONS

d2d	door-to-door Ride-pooling
D-Ride	Dynamic Ridesharing
DRT	Demand Responsive Transit
GPS	Global Positioning System
MaaS	Mobility as a Service
MATSim	Multi-Agent Transport Simulation
MOEs	Measures of Effectiveness
SAV	Shared Autonomous Vehicle
sB	Stop-based Ride-pooling
TNC	Transportation Network Companies
VKT	Vehicle Kilometer Traveled
VMT	Vehicle Miles Traveled
XML	Extensible Markup Language

INTRODUCTION

Background

Shared mobility is a method of transportation that allows the temporary use of various transportation modes by a traveler. Examples include car-sharing, scooter sharing, bike sharing, ride-pooling, and micro transit services [1]. The advancements in information and communication technologies have allowed a wide range of services to be offered to the public in real-time, as well as on-demand [2]. This transportation feature allows users to acquire on-demand access to transportation modes including public transportation. According to Tu et al. [3], the advent of smartphones, the mobile internet, and the use of location-based services has led to a new mode of transportation known as the on-demand ridesourcing service [3]. In recent years, companies like Uber and Lyft have provided smartphone applications to connect passengers with independent drivers. Passengers can request a ride using the mobile application, which transmits their location to available drivers via GPS technology [2]. This new framework has been adopted by transportation network companies (TNCs) such as Uber and Lyft, with the promise of providing an expanded array of transportation options to travelers in their service areas.

Ride requests can either be for individual rides or for shared rides (also known as ride-pooling). Ke et al. [4] defines a ride-pooling service as an on-demand transportation option that pairs unrelated passengers in a single vehicle for a shared ride. The process of matching up riders in ride-pooling services is determined by the riders' origin and destination locations in a way that ensures that everyone can travel together in the same vehicle while maintaining a reasonable travel and delay time. As a ride-sourcing transportation option, ride-pooling has become increasingly popular over the past few years, since multiple passenger requests can be fulfilled in one vehicle, therefore reducing the number of vehicles on the road [4]. TNCs view ride-pooling services as an opportunity to boost their ridership, lower expenses for customers, and broaden the range of ridesharing options available [5]. Ride-hailing companies Uber and Lyft offer their customers Uber Pool and Lyft Line ride-pooling services in many cities worldwide. According to Lo et al. [6], Uber launched its Uber Pool service in 2014 in order to facilitate the sharing of trips with other riders who are traveling in the same direction [6]. Furthermore, drivers benefit from pooled rides as they are able to reduce their operating costs, as well as maximize their income. In an Uber Pool trip as mentioned on the Uber [7] website, Uber determines which route is best for picking up multiple riders.

Even though it is important to understand the true impacts of the use of TNC services on the performance of the transportation network, there are few studies that have examined and documented such impacts. This is attributed to the lack of TNC trip data and the limitations of commercial simulation software with respect to simulating TNC trips along with other available transportation modes. There are many claims that shared mobility and on-demand ridesourcing services benefit customers and can provide congestion relief as users of such services may shift their trips from private automobiles to TNCs or transit. However, it remains unclear how the on-demand ridesourcing services affect travelers' mode choices and transportation network performance, especially in medium-sized cities where TNCs operate.

Problem Statement, Objectives, and Significance

In recent years, researchers and policymakers have debated the impact of transportation network companies (TNCs) on urban congestion. Due to the widespread use of TNCs, particularly Uber and Lyft, two perspectives have emerged regarding how TNC services might affect urban congestion. According to one perspective, TNCs can motivate travelers to abandon their personal vehicles, thereby removing those vehicles from the network and reducing overall congestion levels. They may also provide last-mile connections that would make use of transit more attractive and convenient to transportation users. Another perspective, however, claims that the advent of TNCs actually results in the creation of a new type of TNC users, the TNC drivers, who hover over the network in order to pick up riders. There is a potential that this practice results in a greater amount of time that TNC vehicles spend on the network and higher VKTs, which will increase the level of congestion.

Several studies have highlighted the convenience and flexibility of TNCs as a mode of transportation [2, 8, 9] and others noted the positive effect of TNCs on improving access to transportation for people living in areas with limited public transportation and who do not own a car [2]. Despite the fact that TNCs are capable of reducing the number of vehicles on the road [10], there is also evidence to suggest that they may also reduce public transit ridership, [11] and contribute to increased traffic congestion [11-15].

This study aims to get a clear understanding of the actual impacts on VKT and traffic congestion in the presence of TNC services, and overcome the limitations caused by the unavailability of TNC trip data and the inadequate capacity of commercial simulation software to model TNC trips. To achieve this, the objective of this research is to quantify/document the operational performance impacts of TNC services operating in medium-sized cities using Birmingham, AL as a case study. This is done by (a) collecting TNC trip data directly from Uber/Lyft drivers in the study area; (b) developing a multi-agent transport simulation model that includes individual and ride-pooling TNC trips; (c) incorporating survey data into a simulation model of the study area; (d) using the model to simulate traffic operations for various TNC fleet sizes and document their impacts on traffic network performance; and (e) quantifying the impacts of TNCs on congestion in terms of changes in VKT.

The findings of this study are anticipated to be advantageous for engineers, transportation planners, and policymakers in their evaluation of the impacts of TNC services. The results may aid in the development of policies and regulations that consider the benefits and drawbacks of TNCs for both individuals and communities.

Dissertation Research

The primary goal of this dissertation was to investigate the impact of shared mobility and on-demand ridesourcing services on urban congestion. The research aimed to quantify/document the operational performance impacts of TNC services operating in a medium-sized city, with a specific focus on vehicle kilometers traveled (VKT). This dissertation research considered two TNC services - individual and pooled rides - to understand their impact on traffic congestion.

Chapter 1 of this dissertation highlights the limited understanding of the performance impacts of shared mobility and on-demand ridesourcing services offered by transportation network companies (TNCs). To address this knowledge gap, simulation modeling techniques can provide insights into the impacts of various levels of market penetration of TNC services, given the challenges in acquiring field data. A detailed literature review was conducted and case studies were reviewed in order to identify suitable platforms for modeling shared mobility through the use of simulation tools. A summary of available simulation tools for simulating TNC services is presented in this chapter. Attributes of three simulation platforms, including required skills for users, model development time, input data requirements, modeling level, output data, and simulated modes, were reviewed and contrasted. The findings from this chapter laid the necessary groundwork to develop and conduct the agent-based transport simulation study described in Chapter 2.

In Chapter 2, the primary research objective is to measure the influence of TNC services on traffic operations through the utilization of a MATSim simulation platform. The focus is specifically on evaluating the impact of on-demand ridesourcing services, wherein customers request individual vehicles for each trip request. Travel plans for travelers in the network were generated using synthetic populations since obtaining travel plans for all travelers is challenging. The daily plans of the study area travelers were gathered through an online survey and open-source data, and daily Uber travel plans were derived from the travel logs of local Uber drivers who were recruited for this purpose. The simulation consisted of a baseline condition and three TNC scenarios, involving 200, 400, and 800 active TNC vehicles. MATSim's Taxi Extension was used to incorporate Uber trips into the day plans. The simulation outputs were evaluated to define the ideal fleet size to meet TNC demands at specific times of day and to evaluate TNC operational effects along particular corridors. The evaluation process employed several measures of effectiveness, such as the networkwide VKT and hourly averages for speed, travel time, and volume at four specific locations within the network.

Chapter 3 presents an expanded study described in Chapter 2 to include TNC ride-pooling services and assess its impact on urban traffic congestion using the MATSim simulation tool. In a ride-pooling service (e.g., Uber Pool and Lyft Line), trip requests may be fulfilled simultaneously with a single vehicle (up to 4 passengers in a vehicle). At the time of the study, ride-pooling services were not yet available in the Birmingham metropolitan area. The inclusion of ride-pooling services in the study aimed to examine their potential operational impact if TNCs were to offer the service in the future. MATSim's Demand Responsive Transit (DRT) module was used to simulate ride-pooling scenarios including 200, 400, and 800 TNC vehicles that were added to the network. The study analyzed two types of ride-pooling services: door-to-door (d2d) and stop-based (sB), with a maximum acceptable waiting time of 5 minutes. The study developed six ride-pooling scenarios, consisting of three d2d and three sB scenarios. The results of these scenarios were then compared to the baseline scenario developed in Chapter 2. Various measures of effectiveness were utilized in the evaluation process, including networkwide VKT, TNC total daily distance traveled, vehicles empty ratio, detour distance, and ride request rejection rate.

The results obtained from this dissertation collectively contribute to a better understanding of the potential impacts of TNCs' individual and pooled rides trips and their correlation with travel demand, and traffic operations in a medium-sized city, such as Birmingham, AL. The knowledge gained from this study can be utilized by TNC service providers and local authorities to improve TNC operations and better fulfill the needs of passengers in the future.

CHAPTER 1:

SIMULATION OPTIONS FOR MODELING SHARED MOBILITY

by

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Abstract

Shared mobility and ridesourcing services (such as Uber and Lyft) are emerging transportation options allowing users to gain short-term access to transportation modes on an as-needed basis. In recent years, these transportation options have been adopted at a rapid pace, due to technological advancements and the public's willingness to accept and support sharing economy. However, the full impact of shared economy services on local and regional congestion are not yet understood due to field data acquisition challenges. Thus, a need currently exists to evaluate the impacts of shared mobility on the performance of urban transportation facilities. To achieve this goal simulation modeling should be utilized due to the lack of field data availability. However, traditional traffic simulation models lack the ability to simulate shared modes in detail. Thus, some new simulation platforms have emerged recently that allow shared mobility simulations.

Given the limited experience in this area, an extensive review of the literature and research case studies took place to identify available platforms for shared mobility simulation modeling. This paper documents the findings from a comparative study of three such simulation platforms, namely Multi-Agent Transport Simulation (MATSim-Version 0.8.1), Auto Desk Mobility Simulator, and the Dynamic Ridesharing (D-Ride-Version 1.0) software. The comparison of model capabilities performed in this study identified MATSim as the most promising and well-established available platform. Thus, the paper further explores the key features and capabilities of MATSim for simulating shared modes, along with implementation requirements, limitations, and case studies.

The findings of this study are expected to be of interest to researchers and practitioners in search of reliable simulation tools to model shared mobility modes in

future studies. The study also provides transportation agencies the means to plan mobility as a service (MaaS) where shared mobility and ridesourcing services are available.

Introduction

Shared mobility is a transportation feature that helps riders to gain short-term access to different transportation modes (e.g., car-sharing, scooter sharing, bike-sharing, carpooling, and transit services). It enables users to get on-demand access to transportation modes, including public transportation and shuttles. Several studies reported a reduction in vehicle usage, vehicle ownership, vehicle miles traveled, travel cost savings, and social and environmental benefits resulting from the use of different transportation shared modes. According to RideScout (as cited by Miller, Geiselbrecht, Moran, and Miller (2016)), mobile technology and transportation data accessibility have empowered the advancement of widespread mobile applications that provide real travel time information and enable shared mobility options.

The development of smartphone apps, the explosion of internet use, the availability of GPS location services, and routes optimization have lead innovators to develop new transportation options in order to increase the accessibility, reduce the ownership of vehicles and overall contributed to the advancement of transportation shared modes (Shaheen, Cohen, & Zohdy, 2016). As a result of advancements in technology, shared mobility has grown rapidly since it first launched in North America in 1994. As reported in 2012, an estimated 401 ride-matching services were located in the United States and 261 were located in Canada (Chan & Shaheen, 2012).

While there are many assertions about the likely benefits of shared mobility and e-hailing services, yet the full impacts of such services on transportation network performance are not fully understood. Due to the limited availability of field data, simulation modeling techniques can be employed to quantify such impacts for various market penetration levels of car/ride sharing modes.

This study summarizes the findings from a comparative study of available simulation tools that can simulate car/ride sharing modes based on an extensive review of the literature and research case studies.

Methodology

Recent literature works advocate the use of agent-based simulation models to study ridesharing and how it impacts traffic demand (Ciari, Balac, & Axhausen, 2016);(N. Ronald, R. Thompson, & S. Winter, 2015);(N. Ronald, R. G. Thompson, & S. Winter, 2015);(Ronald, Yang, & Thompson, 2016). Accordingly, this study identified and compared four simulation tools that can simulate shared mobility modes. These were a) the Multi-Agent Transport Simulation (MATSim- Version 0.8.1), b) the Auto Desk Mobility Simulator, and c) the Dynamic Ridesharing (D-Ride- Version 1.0). These simulation platforms implement agent/activity based modeling, data mining and machine learning, and have various advantages and shortcomings for implementation.

The attributes of each simulation platform were reviewed and documented, including the required skills for a user, cost of getting the software, approximate time to develop a base model, user-friendliness, required data/files for inputs, modeling level (Microscopic, Mesoscopic, Macroscopic), output data, simulated modes, simulation architecture, and non-traditional operating conditions.

The most promising simulation platform for evaluating shared transportation modes was identified and explored in greater detail.

Results from Model Comparison

Attributes of 3 simulation platforms identified above were reviewed and summarized in Table 1. Attention was given to the types of modes that can be simulated by each tool, system requirements, model development requirements, user friendliness, modeling fidelity, ability to model dynamic events, and cost. Moreover, input requirement and output capabilities were review and contrasted as shown in Tables 2 and 3 respectively.

The comparison of simulation model capabilities performed in this study showed that the most promising and well-established platform for simulating ridesharing travel options is MATSim (Salman, Sisiopiku, & Ramadan, 2017).

MATSim incorporates time choice, mode choice, and/or destination choice into an iterative loop, leading to a stochastic user equilibrium. Through its computationally efficient-queue based approach, MATSim holds promise toward accurate modelling of technology-based ridesharing modes. Thus, the MATSim model was selected as the best available tool for further investigation.

Table 1

Comparison of attributes of shared mobility modeling simulation tools

Attributes	MATSIm	Mobility Simulator for InfraWorks 360	D-RIDE-AMS
Simulated modes	Car, bike, train, taxi, truck, car/ride share	Car, taxi, bicycle, walking, bus, train	Car-pooling, ride-sharing, vanpooling
Simulation architecture	Multi-agent simulation	Multi-agent/ agent-based model	Activity based model
Pre-requisite skills	Java Prog., XML structures, agent-based	OS, MS Office	OS, MS Office, GIS
System requirements	4 GB RAM and 200 GB free disk space	8 GB RAM,10 GB free disk space, Core i7	MS Windows 7, Visual Studio Libraries
Model development time	Extensive	Low	Low
User-friendliness	Basic GUI without online help	Fully developed GUI, well organized	Good GUI interface, easy to locate tools
Modeling fidelity	Mesoscopic: Medium/high fidelity	Microscopic; High fidelity	Macroscopic; Low fidelity
Dynamic events modeled	Weather conditions, incidents	No	No
Cost	Open-source + €1000 /yr. for Via	$1575 /yr.	Open-source

Table 2

Comparison of input requirements for selected shared mobility modeling simulation tools

MATSim	Mobility Simulator for InfraWorks 360	D-RIDE-AMS
Configuration: Connects other input files, configuration parameters, controllers, etc. **Network**: Nodes & links, coordinates, modes using link, link capacity, speed **Demand**: Travel demand and daily plans (tours) for every agent	**Parameters**: Defines agents' behaviors **Network**: Shows roadways and paths **Control**: Traffic signals, pedestrian crossings **Demand**: Trips, origin, destination **Trips**: List of trips, agent, origin, destination, and departure time **Validation**: Validate model performance	**Agent data**: Demand, origin, destination, departure and arrival times, capacity **Configuration data**: Iterations, shortest path, vehicle cost/hr **Link data**: Id, start/end node, type, direction, length, lanes, speed limit, capacity **Node data**: Node id, coordinates

Table 3

Comparison of outputs for selected shared mobility modeling simulation tools

MATSim	Mobility Simulator for InfraWorks 360	D-RIDE-AMS
• Score Statistics (.png): show the avg. best, worst, executed and overall avg. of all agents' plans for every iteration. • Leg Travel Distance Statistics (.png): plot travel distance • Events (XML): activity start or change, important base for post-analyses • Plans (XML): the current state of the population with their plans • Leg Histogram (.png): agents arriving, departing or en-route, per time unit • Trip Durations (.txt): listing number of trips and their durations • Link and Network Stats (.txt): count values, travel times, emissions Accessibility measures	• Summaries for People/ Cyclists/ Public Transport/ Private Vehicles/ Freight: • Distance (m), time (sec.), stops for each mode (number of stops) • Modes includes walking, passenger, driving, waiting • Lane changes • Loop activations • Emissions (CO2 (kg/ton), NO (g/ton), PM10 (g/ton)) • Detailed Public Transport Information • Economic Evaluation (detailed costs for each trip) • Level of Service Reports	• AgentPlus: suggests vehicle's pickup, delivery sequence, and corresponding paths to satisfy passengers' needs while minimizing the overall cost. • DTALite: determines the best dynamic pricing strategy for vehicles, for sustainable development of D-RIDE applications. • Agent routing • Agent scheduling: a path containing a sequence of time stamps • Assignment of vehicles to passengers • Updated agent serving value ($) • Upper bound, Lower bound, and gap % between them

Review of MATSim Features

MATSim is a non-traditional, open source simulation platform implemented as a Java application that provides a framework to perform large-scale agent-based transportation simulations of various transportation modes, including shared modes. The framework consists of several modules which can be combined or used as stand-alone. Currently, MATSim offers a framework for demand-modeling, agent-based mobility-simulation (traffic flow simulation), re-planning, a controller to iteratively run simulations as well as methods to analyze the output generated by the modules (Sisiopiku, Hadi, McDonald, Steiner, & Ramadan, 2019).

The platform adopts the activity-based approach to generate agents' activities.

Within the context of MATSim, agents are the individual travelers, and agent behavior refers to an individual's daily activity travel plan and route choice.

MATSim designs two layers: a) the physical layer, which simulates the physical world where the agent (or traveler) moves, and b) the mental layer, in which the agents generate strategies, including routes, mode choice, and daily activity plans. MATSim runs its activity plan, microsimulation, activity re-plan, microsimulation, and so on, iteratively until it reaches a stationary state of the system, where an agent cannot improve its score by revising the plan. The MATSim simulation steps are listed below:

- A set of initial plans is generated.
- The plan selection mechanism of the agent database chooses one plan per agent for execution.
- The model runs the simulation to execute the plans, produce a new travel time for each trip, and re-score the plans.
- A subset of the agents is chosen to undergo plan adjustment or new plan generation by external strategy modules.
- The model runs external strategy modules, and each agent is updated with a new or revised plan.
- The model runs the mode and route choice module to produce a route for each agent.
- If the stop criterion is satisfied, then the simulation stops; otherwise, the process continues for additional iterations, as needed.

MATSim Capabilities and Requirements

The MATSim tool is designed to simulate large-scale scenarios by adopting a computationally efficient queue-based approach (Horni, Nagel, & Axhausen, 2016). It incorporates mode/time choice, and/or destination choice into an iterative process loop by removing the lowest score plan until the average plans become steady.

A MATSim run contains a number of replications starting with an initial demand that emerged from the travel diaries for travelers in the study area. Activity chains are derived from empirical data through sampling or discrete choice modeling to establish the initial demand. The initial demand is optimized individually for each traveler during iterations. Each traveler selects a plan prior to simulation in each iteration, the selection is dependent on plan scores, which are calculated after each mobility simulation (mobsim) run based on plan performances. MATSim replanning module is performed to modify travel plans by considering four dimensions: departure time, route, mode, and destination (Horni et al., 2016). The MATSim loop is demonstrated in Figure 1 below.

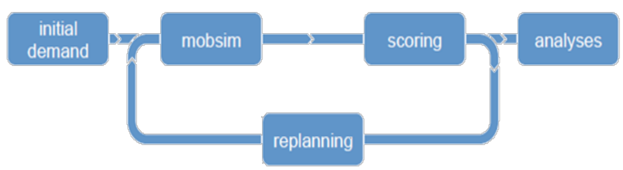

Figure 1. MATSim loop
(Source: MATSim Book 2016, p. 5).

The Traffic Flow Model in MATSim provides two internal Mobility Simulations (mobsims), namely Queue Simulation (QSim) and Java Discrete Event Queue Simulation (JDEQSim), Figure 2 below shows the traffic flow model developed by MATSim.

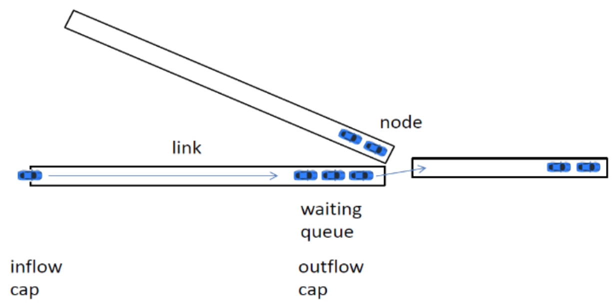

Figure 2. MATSim traffic flow model
(Source: MATSim Book, 2016, p. 6).

The MATSim traffic flow model works based on two link attributes, namely storage and flow capacity. Storage refers to the number of vehicles that can fit onto a network so that vehicles can only enter a link when a link is not full. Flow capacity refers to the outflow capacity of the section, e.g. number of vehicles that can leave the section per time. Accordingly, vehicles can only leave a section of the road when the volume does not exceed the outflow capacity.

MATSim optimization is performed in terms of agents' plans scoring based on a co-evolutionary algorithm (which leads to a stochastic user equilibrium) until reaching an equilibrium (Horni et al., 2016).

Typical Model Input

MATSim is an open source software that requires its input files to be as Extensible Markup Language (XML) files. Minimum input files required to run the software are:

- Configuration file
- Network file
- Population/plans file

The configuration file builds the connection between MATSim tool and all other XML files (e.g. network, population, etc.), and contains a list of settings that influence how the simulation behaves.

MATSim's network file consists of nodes and links. It is the infrastructure on which agents can move around. Nodes are defined by coordinates while the link requires the definition of several attributes including the length of the link, capacity, speed, and the number of lanes that modes used.

The population file provides information about travel demand, e.g. a list of agents and their travel diaries. The travel demand is described by the daily plans of each agent. The population file contains a list of transportation users and their daily plans, activities, and legs.

It should be noted that since it is practically impossible to get detailed activity-based data for the whole population in any study area, a population synthesis is needed to create the population data based on a sample of data (e.g. travel dairy survey data) using modeling techniques that mirror the true population. Hence, modelers opt for population syntheses based on travel diary surveys, land use data, and census data. The most prominent techniques are iterative proportional fitting (IPF), iterative proportional updating (IPU), combinatorial optimization, Markov-based, fitness-based synthesis, and other emerging approaches. A critical review of the literature on population synthesis options by (Ramadan & Sisiopiku, 2019) provide details regarding this topic.

MATSim Typical Outputs

Typical output files from MATSim include the following (Horni et al., 2016):

- Log File: contains information needed for analyses or debugging

- Warnings and Errors Log File: identifies problems in the simulation
- Score Statistics: shows the average best, worst, executed and overall average of all agents' plans for every iteration
- Leg Travel Distance Statistics
- Stopwatch: contains computer time
- Events: records every action
- Plans: contains the final iteration plans
- Leg Histogram: describes the number of agents arriving, departing or en route, per time unit
- Trip Durations
- Link Stats: contains hourly count values and travel times on every network link

MATSim Limitations

Discussing the limitations of the MATSim platform, (Ciari et al., 2016) suggest that MATSim's behavioral model assumes homogeneity in evaluation criteria for travelers regarding car-sharing and all other modes, thus, not capturing the individual or average preferences (Sisiopiku et al., 2019).

An additional limitation is the extent to which MATSim is able to differentiate between different activities, which may need further refinement to sufficiently model car-sharing usage. As (Ciari et al., 2016) explain, car-sharing is known to fluctuate throughout the week, yet MATSim is limited to only single day simulations. Thus, the authors conclude that "the properties of agent-based modeling are particularly suitable to assess hypothetical scenarios on which limited previous knowledge is available, yet long-term effects of car-sharing are beyond the scope of the simulation" (Ciari et al., 2016).

Despite its current limitations, MATSim is ideally situated to evaluate future circumstances through assumed behavioral changes, although some additional work is needed on the behavioral model (Ciari et al., 2016). Even in its current form MATSim can help to assess how different operation strategies would work and how demand would be modified as a result of shared economy applications. Furthermore, it can already account for mode substitution based on supply characteristics (Ciari et al., 2016).

Case Studies

Simulation of shared mobility services is a relatively new concept and only a few studies exist in the literature focusing on limited applications and studying their impacts. Most of these studies used agent-based simulation platforms such as MATSim for modeling and analysis purposes. MATSim dynamic traffic assignment and activity-based models were used in Toronto, Canada to simulate the impacts of different policy interventions to meet atmosphere changes objectives by 2031. MATSim dynamic traffic assignment with activity-based travel demand modeling has likewise been incorporated in Dallas-Fort Worth, TX, Tel Aviv, Israel, in Austin, TX, and Los Angeles, CA. MATSim is the only dynamic traffic assignment tool used for large-scale and regional simulation since it uses detailed travel activities, and spatial queue models (Alemi & Rodier, 2016).

Many simulation efforts were geared towards understanding congestion issues and their ensuing negative externalities. One such example comes from (Bischoff & Maciejewski, 2016), who studied congestion impacts of both real-time autonomous taxi operation and mixed autonomous/conventional vehicle traffic flow using MATSim (Bischoff & Maciejewski, 2016). To provide a comprehensive analysis of impacts from autonomous taxi fleets, the authors use various replacement ratios to estimate potential effects for different stages of inception From their simulation results, (Bischoff & Maciejewski, 2016) suggest potential positive traffic benefits from large-scale AV taxi fleets in cities with one autonomous taxi replacing between 10 and 12 conventional vehicles. The authors further found that proximity to the city center shows more significant positive benefits than moving further away (Bischoff & Maciejewski, 2016).

Dubernet, Rieser-Schüssler, and Axhausen (2013) utilized MATSim to simulate the feasibility of carpooling in Zurich, Switzerland area. The study found more than 87% of trips could be coordinated in a two-riders carpool. The study found more than 47% of trips could be coordinated in a two-riders carpool if the trips were individual.

Fagnant, Kockelman, and Bansal (2015) investigated the potential operational and environmental impacts of shared autonomous vehicle (SAV) fleets by simulating shared autonomous vehicles in 12-mile by 24-mile region in Austin, Texas. The study utilized the MATSim to evaluate 100,000 trips that were randomly selected out of 4.5 million trips in Austin, Texas. The study found that each SAV can replace 9.3 conventional vehicles within the 12-mile by 24-mile region. The study also reported that total parking demand would be reduced by 8 vehicles for every SAV use, which in return will reduce the land use requirements for parking services. The study further reported a reduction in cold starts emission by 85% due to replacing conventional vehicles.

These studies provide examples of the range of applications of the MATSim model and its usefulness toward assessing the impacts of the implementation of emerging transportation modes on travel demand and urban congestion in the era of share mobility and Mobility-as-a Service (MaaS).

Discussion and Conclusion

The literature review identified three simulation platforms that showed promise toward simulating of shared mobility options. These platforms, namely MATSim (version 0.8.1), Auto Desk Mobility Simulator, and Dynamic Ridesharing (D-Ride) (version 1.0), where compared in an effort to assist future users with the platform selection task.

The comparison of model capabilities performed in this study based on features and earlier case studies showed that the most promising and well-established platform is MATSim. It incorporates time choice, mode choice, and/or destination choice into an iterative loop, leading to a stochastic user equilibrium. Through its computationally efficient-queue based approach, MATSim promises accurate modelling of technology-based car/ridesharing modes. While work is still needed to address current limitations, case studies that utilized MATSim in the recent years to model shared mobility options show great promise.

The findings of this study are expected to be of interest to researchers and practitioners that are in search of reliable simulation tools to model shared mobility options and assess their impacts on transportation network operational performance.

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CHAPTER 2:

QUANTIFYING THE IMPACT OF TRANSPORTATION NETWORK COMPANIES ON URBAN CONGESTION IN A MEDIUM SIZED CITY

by

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Abstract

In the recent years, TNCs (transportation network companies) and on-demand ridesharing services have grown rapidly. Given conflicting reports on TNC impacts, a need exists to study mode choice shifts in the presence of TNC services and their effects on urban congestion. Using Birmingham, AL (Alabama) as a case study, this paper showcases the feasibility of modeling TNC services using the MATSim (Multi-Agent Transport Simulation) platform, and evaluating the impact of such services on traffic operations. Data used for the study were gathered from Uber drivers and riders through surveys, as well as the US Census. The results indicate that when 200, 400, and 800 TNC vehicles are added to the network, the VKT (vehicle kilometers traveled) increase by 22%, 23.6%, and 23.2%, respectively, compared to the baseline scenario (no TNC service). Analysis of hourly average speeds, hourly average travel times, and hourly volumes along study corridors further indicate that TNC services increase traffic congestion, in particular, during the AM/PM peak periods. Moreover, the study shows that the optimal TNC fleet size for the Birmingham region is 400 to 500 active TNC vehicles per day. Such fleet size minimizes idle time and the number of TNC vehicles hovering, which have adverse impacts on TNC drivers, and the environment while ensuring TNC service availability and reasonable waiting times for TNC customers.

Introduction

The availability of the GPS (global positioning system) and wireless services and the increase in the use of smartphones have contributed to the establishment of a new shared transportation mode option called on-demand ridesourcing. Within this new framework, TNCs (transportation network companies) such as Uber and Lyft promised to offer additional choices to travelers in their service area and even relieve the strain on existing transportation networks from automobile use [1]. However, to date, the impact of these services on travelers' mode choices and transportation network performance is not clear.

The proliferation of TNCs, mainly Uber and Lyft, developed two perspectives on the potential impact of TNCs on urban congestion. The first perspective argues that TNCs motivate travelers to abandon their personal vehicles thus taking off vehicles from the network, which can result in lower levels of congestion and a reduction in the total VKTs (vehicle kilometers traveled). The second perspective claims that TNCs created a new group of transportation network users, the TNC vehicle drivers, who hover the network in an effort to pick up riders. This practice has the potential to increase the time that TNC vehicles occupy the network and VKTs, which in turn results in higher levels of congestion.

Despite the importance of understanding the true impacts of TNC services on transportation network performance, limited studies are available that examined and documented such impacts. This is attributed to two main reasons: first, the lack of available TNC trip data which TNC operators are reluctant to share citing privacy concerns, and second, the lack of commercially available simulation software programs that can be used to simulate TNC trips in conjunction with other transportation modes.

The Birmingham, AL (Alabama) case study presented in this paper addressed those limitations by (a) collecting TNC trip data directly from Uber/Lyft drivers in the study area, (b) incorporating such data into a comprehensive agent-based simulation model of the Birmingham region, and (c) using the model to simulate traffic operations for various TNC fleet sizes and document their impacts on traffic network performance. This work builds on our earlier research efforts to develop a prototype agent-based model for the city of Birmingham [2] and incorporate public transit and shared mobility options in the same network [3-5]. In this study, we introduce innovative methods to extract detailed trip information from Uber/Lyft driver trip logs and to generate realistic travel plans of the Birmingham MATSim (Multi-Agent Transport Simulation) simulation model that incorporated TNC trips along with automobile, public transit, and walking trips. The Birmingham MATSim model was then used to simulate scenarios that incorporated various TNC fleet sizes. This allowed us to quantify the impacts of expanding TNCs fleet sizes on congestion in terms of changes in VKT, average speeds, average travel times, and hourly volumes along study corridors and the network as a whole.

Literature Review

The literature review identified several research studies that documented (a) transportation users' preferences, attitudes, and practices toward TNC use based on questionnaire surveys, and (b) impacts of TNC service presence on traffic operations and traffic congestion. Representative studies are discussed next.

Users' Mode Choices and Attitudes toward TNCs

Rayle et al. [6] conducted a study in the San Francisco area to understand preferences and use of TNC services in the region. Results from an analysis of 380 responses to a questionnaire survey revealed that UberX provided the majority of the rides (53%), followed by Lyft (30%). With respect to the purpose of the trip, 67% of trips were for social reasons, 16% were for work purposes, 4% were rides to/from airports, 3%

were for shopping, and 10% were for various other destinations (e.g., medical, to/from transit). If TNCs were unavailable, 39% of the people surveyed would take a taxi, 33% use transit, 8% walk, 6% would drive their own vehicles, 2% would use bikes, and the remaining 12% would use other modes of transportation. The study documented TNC users' choices, but reported that the impact from TNCs on VKT remains uncertain.

Bekka et al. [7] analyzed survey responses from 1,966 Uber users in order to determine the effect that Uber had on car ownership in the Paris metropolitan region. According to the survey responses, 17% of households that had used Uber in the last four years had eliminated at least one personal vehicle due to TNC service availability. Furthermore, an investigation was conducted by Clewlow et al. [8] to examine users' behaviors and attitudes toward the use of shared mobility services. It was reported that 26% of individuals expressed that they had lowered their driving distance by 10 miles every week since they began using ride-hailing services.

TNC Services' Impacts on Traffic Operations

According to Qian et al. [9] there has been a continuous deterioration in traffic conditions in NYC (New York City) at different day times and locations based on two years of data analyzed linked to the availability of FHVs (for-hire-vehicles). The study reported an increase of over 48% in FHVs between 2017 and 2019 coupled with a 22.5% reduction in speed recorded in NYC on weekdays during the same time period. This conclusion is consistent with findings from Erhardt et al. [10] and Roy et al. [11] who examined the correlation between the TNCs advent and congestion increase in San Francisco between 2010 and 2016. Erhardt et al. [10] concluded that the presence of TNC vehicles on San Francisco's streets contributed to an increase in delay for automobile users on weekdays by 62% in 2016, compared to 2010. Roy et al. [11] also reported that TNCs were responsible for 47% of the increase in VMT (vehicle miles traveled) and that they were primarily responsible for nearly half of the congestion increase observed in San Francisco during the study period. A study by Henao and Marshall [12] in the Denver region also estimated that the presence of TNCs contributed to an increase of approximately 83.5% in the number of vehicle miles driven compared to the number of VMT without the presence of TNCs. The authors attributed this sharp increase to mode replacement and driver deadheading. Tirachini et al. [13] investigated the impact of TNCs on VKT by using a Monte Carlo simulation model and inputs from a questionnaire survey of 1,600 responders mostly from Santiago, Chile. The results of the study confirm that TNC services increased VKT as a result of modal shifts from transit or generation of new trips by the TNCs. To avoid increases in VKT, the authors suggest that the average occupancy rate of ride-hailing trips should exceed 2.9 persons/veh. Beojone and Geroliminis [14] examined the effects of increasing the size of TNC fleets on urban congestion using the city of Shenzhen, China, as a case study. As fleet size increased from 1,000 to 7,000 vehicles, a reduction in waiting times to pick up riders was observed. However, the fleet size increase also intensified congestion, which, in turn, prolonged the total travel time. Li et al. [15] proposed two hypotheses: (a) the introduction of Uber reduces traffic congestion in urban expanded areas, and (b) the introduction of Uber increases traffic congestion in compact areas of metropolitan areas. A difference-in-differences method using a unique dataset was utilized by the authors to test those hypotheses. According to the study findings, rideshare services are significantly associated with an increase in traffic congestion in compact areas. Besides, the study found some indications that ridesharing services are related to a decrease in traffic congestion in sprawling metropolitan areas.

It is worth noting that most studies on the impact of TNC services on traffic operations were conducted in big cities such as NYC [9], San Francisco [10], Shenzhen [14], and suggest that TNC services intensify congestion. However, there is a need to examine whether TNC services impacts are similar in moderate-sized cities, as well. The aim of this paper is twofold: (a) to develop a mesoscopic agent-based simulation model including the TNC module; and (b) to quantify the impacts of TNCs fleet sizes on congestion in Birmingham, AL, a medium-sized city where Uber and Lyft services are available.

Methodology

Study Approach

Simulation modeling was employed in order to quantify the impacts of TNC operations on the performance of the Birmingham transportation network under various TNC fleet sizes. First, an appropriate simulation platform had to be selected. Then the simulation model had to be developed, tested and refined to allow for the modeling of TNC trips. Data had to be collected to properly reflect the study network characteristics, and travel demand. Scenarios were developed and used to simulate traffic operations for (a) baseline conditions (without TNC operation) and (b) with TNC service availability for a variety of TNC fleet sizes (i.e., 200, 400, and 800 TNC vehicles). Finally, the simulation outputs were analyzed to determine the optimal Uber/Lyft fleet size to serve the TNC needs in the Birmingham region by hour-of-the-day and the impact of Uber trips on traffic operations along selected corridors.

Simulation Model

Earlier research by the authors compared various transportation simulation options in terms of their features, capabilities, and limitations [16] and concluded that the MATSim platform is the most promising and well-established traffic simulation platform available for modeling ridesourcing and shared mobility services (such as Uber and Lyft). Consequently, the MATSim simulation platform was adopted in this study to simulate the impact of TNC services on traffic operations in Birmingham, AL.

MATSim is an open-source software that requires: (a) a configuration file; (b) a network file, and (c) a population/plans file in order to run. The configuration file contains a list of settings that influence how the simulation behaves. The network file defines the transportation network nodes and links. Coordinates are used to define the nodes and attributes are described for each link including the link length, number of lanes, capacity, and speed. The population file provides information about travel demand which is described in terms of daily plans of each agent (traveler). The population file contains a list of transportation users and their daily plans, activities, and legs.

MATSim simulates the population's travel plans on an underlying road network. MATSim's simulation job is run in iterations as shown in Fig. 1. In order to start the analysis, MATSim requires inputting the initial population demand (also known as plans), in the study area. During each iteration, MATSim executes its "mobsim" simulation executor and runs the selected plans of the agents on the roadway network. Following the execution of each plan, a score is assigned based on the experiences of the agent and the performance of the plan. Based on the plan scores in each agent's plan, a plan is selected for each agent in the replanning step, and this plan may be modified for execution in the next iteration.

At the last iteration, a linkstats file is generated that provides hourly trip counts and travel times for every network link at user specified intervals. This feature allows for the evaluation of the operational performance of individual links, in addition to the study network as a whole. Details about MATSim are available in Horni et al. [17] and online at https://www.matsim.org/.

To speed up the computational performance, and similar to earlier studies that used the MATSim platform [5, 18, 19], 10% of the total population was used for the simulation. Thus, for the Birmingham MATSim model, plans were executed using a population size of 69,826.

In order to effectively implement the MATSim platform for traffic simulation modeling, it is essential to generate a realistic synthetic population and their daily travel plans. The authors used a combination of user surveys and public data sources to generate realistic day plans for the Birmingham network. Starting with automobile trips first, the simulation model was then enhanced to incorporate public transportation trips [2, 20, 21]. In this study, the Birmingham MATSim simulation model was further upgraded to incorporate Uber trips into the day plans. This was achieved by utilizing the Taxi extension in MATSim (org.matsim.contrib.taxi). As available TNC services in Birmingham did not offer ride sharing options such as Uber Pool or Lyft Line, the Taxi extension was selected over the DRT (demand responsive transport) as it closely modeled the local TNC operations. In order to utilize this extension, the authors had to specify the number of Uber/Lyft drivers as well as their starting location. More details on this effort are available in [22]. These model upgrades and extensions resulted in a comprehensive Birmingham MATSim model capable of generating realistic background automobile traffic, TNC trips, as well as transit and walking trips and suitable of meeting the modeling needs of this study.

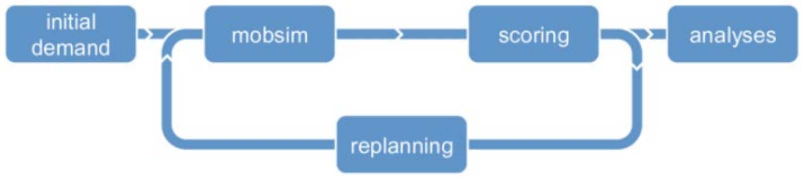

Fig. 1 The co-evolutionary algorithm of MATSim [17].

Data Collection

Due to the difficulty in obtaining TNC trip data for the Birmingham region directly from Uber and Lyft, the research team recruited local Uber drivers and worked with them to extract trip records from their logs. In doing so, a brief questionnaire survey was developed and used to: (a) provide information about the study including survey purpose, compensation, privacy considerations, and consent for participation, and (b) verify eligibility and enroll interested Uber drivers to the study. To be eligible for participation, drivers had to have driven Uber/Lyft in the Birmingham metropolitan region (Jefferson and Shelby counties) during 2019 and/or 2021, prior and after the surge of the COVID pandemic.

After signing up, drivers met in person with trained study personnel who manually captured and stored screenshots of each Uber trip in the Uber app. Each image captured provided exact information about the trip date, start and end time of the trip, trip duration and approximate location of the trip's origin and destination. The data collection yielded a total of 4,229 Uber trip records. A spreadsheet was prepared and used to record information about the study participants and to document their trip records by year and month.

The data captured required detailed post-processing in order to determine the GPS coordinates of the origin and destination (O-D) of each trip based on the trip details and map provided in the image. Georeferencer2 was used for easy image-to-map alignment. The coordinates of trajectory points were extracted directly from the map after it was aligned with the screenshot image with the help of crowdworkers. Detailed crosschecking of the information entered ensured that the proper addresses were captured and all data were entered accurately in the spreadsheet. A total of 3,922 Uber trip records remained in the database after removing trip records that were missing destination information as well as canceled rides.

The study network for Birmingham, AL metro area was obtained using OpenStreetMap and then converted into MATSim nodes and links with the help of the MATSim plugin in Java OpenStreetMap Editor. Despite the wide use of the WGS84 (World Geodetic System 84) coordinate system (e.g., GPS data), the complexity of the WGS84 makes it unsuitable for MATSim due to the difficulty of calculating the distance between points [23, 24]. Earlier studies [24, 25] recommended the UTM (Universal Transverse Mercator) coordinate system, which was adopted for this study. Accordingly, the Birmingham metro area is located in zone 16 north of the UTM coordinate system.

The use of synthetic population to generate travel plans for travelers in the network is a result of the difficulty in obtaining travel diaries for all travelers in the network (population). In this study, we used daily diaries from 451 travelers in the

Birmingham metro area to generate the daily plans of travelers along with open-source data sources, such as the US Census data, OpenStreetMap, OpenAddresses, and the Birmingham Business Alliance. The PDFs (probability density functions), and KDE (kernel density estimation) were applied to generate travel plans that utilized these open data sets to create a realistic population [20, 21]. The synthetic population process has been extended by Khalil et al. [22] to incorporate Uber travel daily plans based on the travel logs of local Uber drivers. As a result of the Uber driver survey, valid trajectories were used to generate the daily plans for TNC drivers [22].

Experimental Design

In spite of the lack of detailed TNC data from the Birmingham region, we estimated the TNC ridership to be approximately 3,500 TNC trips/day. Thus, we generated 3,200 initial TNC trip plans over the 24-h simulation. In our simulation experiments, we varied the number of Uber drivers from 0 to 800. In addition to the baseline scenario (i.e., 0 Uber drivers; no TNC service), three scenarios were considered in detail with gradually increased Uber fleet size (200, 400, and 800 Uber drivers respectively). The simulation of these scenarios allowed for the comparison of outputs, which enabled the identification of the optimal TNC fleet size and quantification of the impacts of TNC presence on traffic congestion. VKT over the entire study network, along with hourly average speeds, hourly average travel times, and hourly volumes at select network locations were used as MOEs (measures of effectiveness) for the evaluation of the designated scenarios. The results are summarized next.

Results

Impact of Number of Drivers on TNC Service

Fig. 2 shows Uber ride plans in the presence of 200 and 400 active Uber drivers in Birmingham. En route, departing, and arriving Uber rides during each hour of the day are clearly marked (green, red, and blue lines, respectively). Each MATSim simulation accounts for trips that have taken place during a 24-h period. Thus, during the simulation model set up, Uber drivers have been set to stop working after the 24th hour of the day. This is reflected in Fig. 2 by the number of en route plans remaining unchanged after the end of the 24-h study period (i.e., green curve becomes flat). When a fleet of 200 Uber drivers is available on a given day, approximately 500 ride requests cannot be satisfied at the end of the day. Thus, in order for all customer ride requests to be accommodated by the end of the day, a minimum fleet of 400 Uber drivers should operate per day in Birmingham.

Fig. 3 shows the variation of TNC vehicle status from hour to hour in the presence of varying TNC fleet sizes (i.e., 200, 400, and 800 active TNC vehicles). At any point in time, a driver may be on an empty drive, occupied drive, picking up, dropping off, or idle. When 200 TNC vehicles operate in the network, we see that nearly all TNC vehicles are occupied (gray), between 8 AM and 9 PM. Most of the TNC drivers are on idle (green) and tend to stay at their last drop-off location outside of those hours. When 400 TNC vehicles operate in the network, nearly all TNC vehicles are occupied between noon and 8 PM, whereas during the morning hours many TNC vehicles are not occupied. A similar trend can be seen when 800 TNC vehicles operate in the Birmingham network, with a peak that can be seen between 4 PM and 7 PM. In order to strike a balance between reducing the drivers' idle time and ensuring TNC service availability with reasonable waiting times in the region, a fleet of 400 to 500 TNC drivers is deemed optimal in Birmingham and medium-sized cities with similar travel demand characteristics.

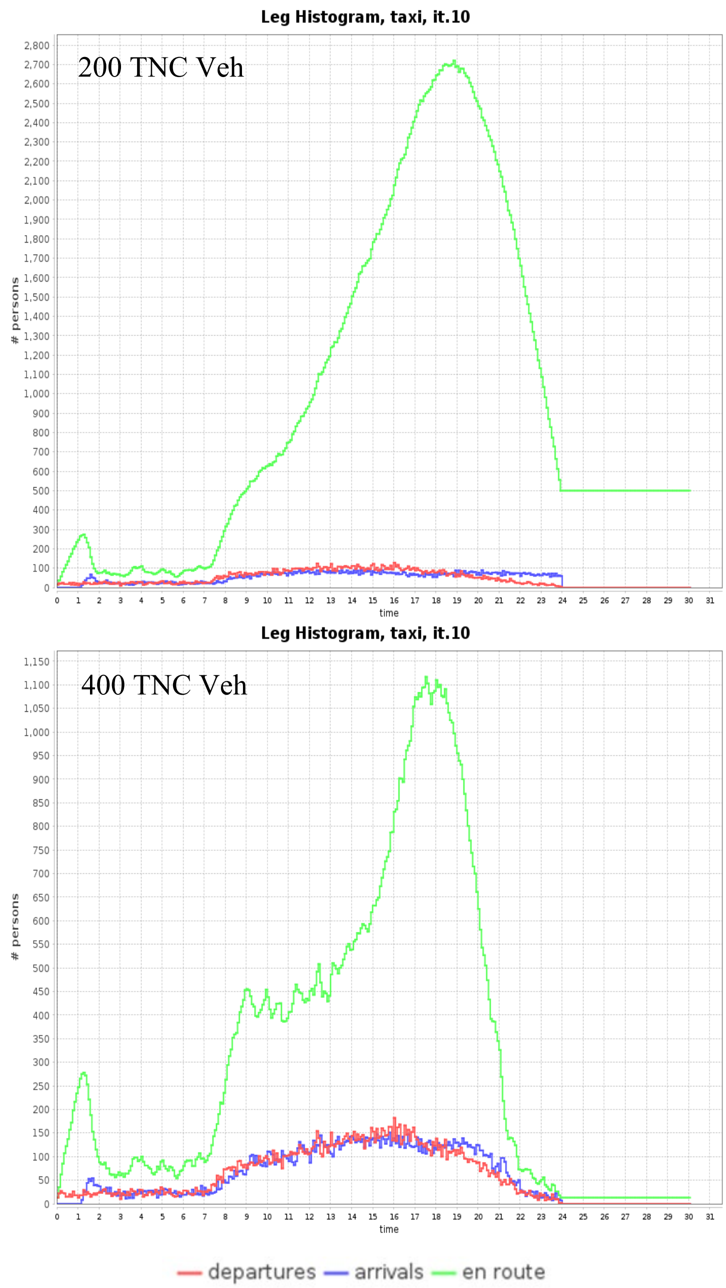

Fig. 2 Number and status of Uber rides by hour.

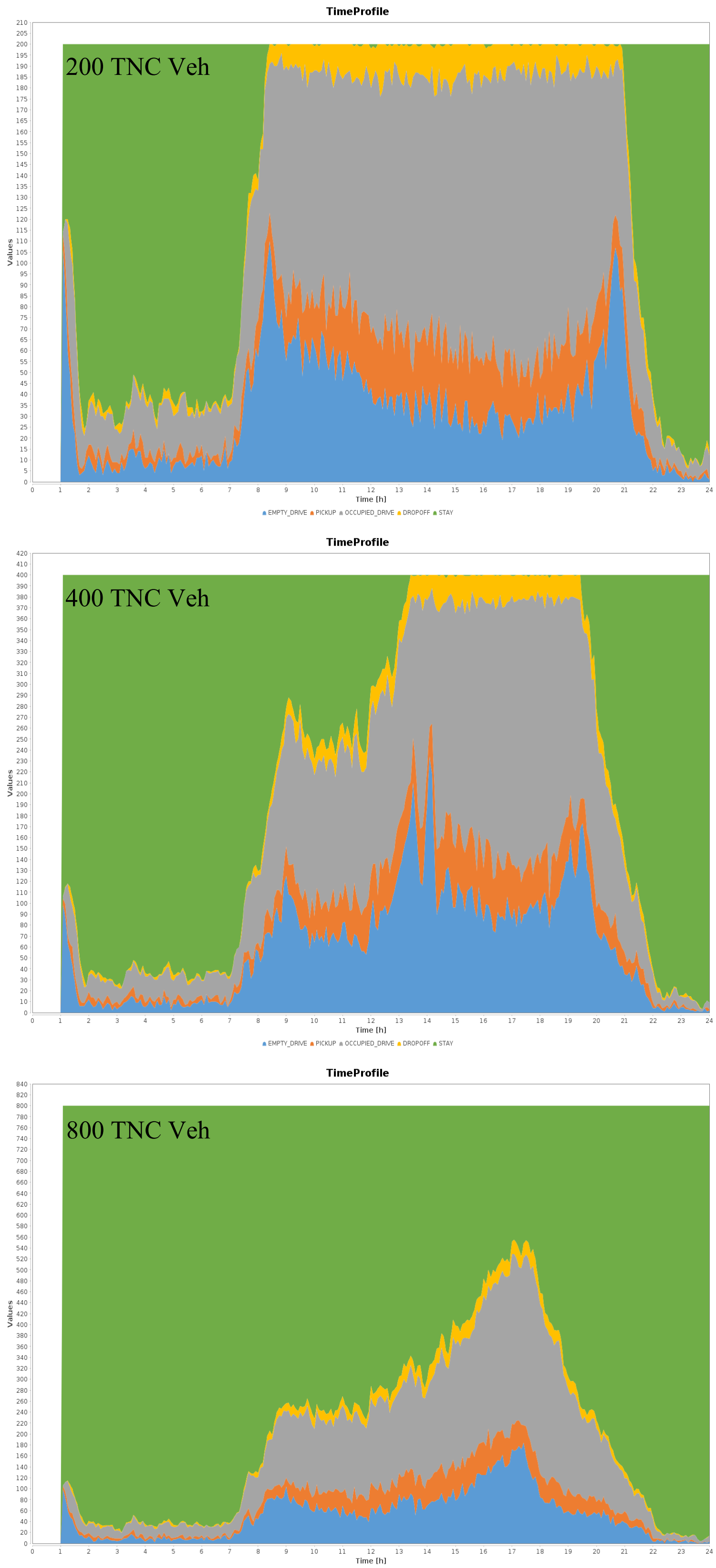

Fig. 3 TNC vehicle status statistics.

Impact of TNC Service Availability on Modal Choice

Table 1 summarizes the distribution of trips by mode for the four study scenarios (0, 200, 400, and 800 TNC vehicles) considered in the Birmingham study. A total of 151,834 plans were generated in the baseline scenario that were distributed between transit, walk, and private automobile modes. Over 144,000 trips were performed by private automobiles (94.85% of total). This is consistent with earlier studies in the Greater Birmingham region including a 2016 commuter survey by Sisiopiku et al. [26] that reported that over 90% of transportation users travel by private automobile. As Table 1 shows, the introduction of TNCs led to a shift of trips from private automobiles to other modes, including TNC trips. This resulted in a reduction of private automobile trips to 127,440 (84.08%). However, when adding the TNC trips, which are also vehicle trips, the total trips by private automobile and TNC combined reached 139,399 (91.98% of total) under the 200 TNC vehicle scenario. This reflects a reduction of 3.2% of the total number of car trips (i.e., private automobile and TNC combined) as compared to the baseline. It should be noted that as TNC vehicles increase to 400, the TNC trips also increase, leading to a total of 143,981 trips by private automobile and TNC combined. This reflects a negligible change in the total number of car trips as compared to the baseline. Further increase of the TNC fleet size to 800 vehicles resulted in an increase in TNC trips and the total trips by private automobile and TNC combined. The simulation results show that the increase in TNC trips as the number of TNC drivers increases from 400 to 800 is small (from 16,540 to 17,092, or 3%). This indicates that the demand for TNC service has almost reached a saturation point below a TNC fleet size of 800 and that adding more TNC vehicles to the network would not benefit the TNC provider or the users. One can conclude that the optimal number of TNC vehicles for the Birmingham network is just over 400, both in terms of transportation network operation and potential benefits for TNC providers.

Table 1

Statistics of executed plans-trips by mode.

Scenario	No. of TNC vehicles	Transit trips	Walk trips	Private auto trips	TNC trips	Trips by private auto and TNC combined	Change in private auto and TNC trips (Baseline: TNC)	% Change total private auto and TNC trips to baseline
Baseline (No TNC)	0 TNC	2,648	5,172	144,014	-	144,014	-	-
TNC service available	200 TNC Veh	3,837	8,317	127,440	11,959	139,399	4,615	-3.20%
	400 TNC Veh	2,532	5,124	127,441	16,540	143,981	33	-0.02%
	800 TNC Veh	2,312	4,806	127,432	17,092	144,524	-510	0.35%

Impact of TNC Service Availability on Network-Wide Operations

VKTs

Using MATSim network wide outputs and Eq. (1), the total daily VKT was calculated for each TNC fleet size scenario. The results are summarized in Table 2.

$$VKT_{Day} = \sum_{h=0}^{h=23} Vehicle\ Count\ /Hour\ x\ \frac{Link\ Length\ (m)}{1000\,\frac{m}{km}} \quad (1)$$

Compared to the baseline scenario, an increase in the total VKT was observed when TNC service was available, ranging from 22.0% to 23.6% for 200 to 800 TNC vehicles respectively. Further analysis indicated that the total hourly VKT for TNC vehicle scenarios peaked during the AM and PM traffic peak periods (7 to 9 AM and 4 to 6 PM), compared to the baseline scenario (Fig. 4) and the differences in VKT from one scenario to another were small.

Table 2

Total daily VKT for each scenario.

Scenario	No. of TNC vehicles	Total daily VKT	Change in total daily VKT (Baseline: TNC)	VKT % diff. to baseline
Baseline (No. TNC)	0 TNC	2,265,716	-	-
TNC service available	200 TNC Veh	2,764,169	-498,453	22.0%
	400 TNC Veh	2,801,092	-535,376	23.6%
	800 TNC Veh	2,790,519	-524,803	23.2%

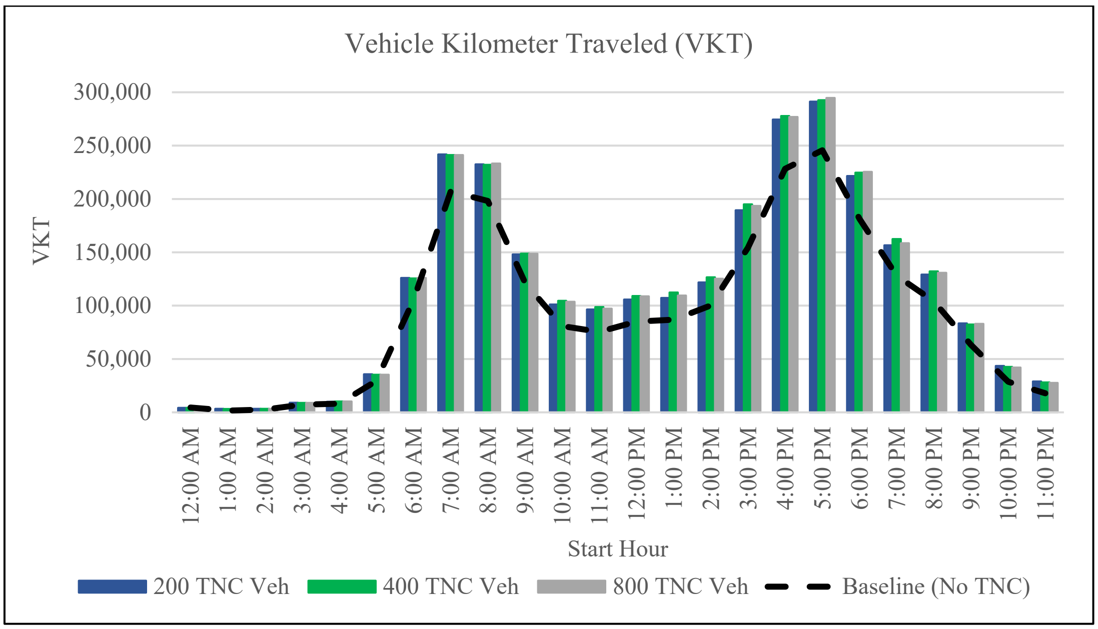

Fig. 4 Total VKT by hour of the day.

Impact of TNC Service Availability on Corridor-Specific Operational Performance

MATSim simulation outputs were also used to evaluate the operational performance of a number of network links under baseline conditions as well as in the presence of TNC service. The operational performance was assessed in terms of hourly average speeds, hourly average travel times, and hourly volumes. The linkstats file in the MATSim output was used to obtain the hourly average travel times and hourly volume for all the corridors within the study. The hourly average speeds for each corridor were calculated as a function of the hourly travel time and the link length along each corridor. As shown in Fig. 5, a sample of four study corridors was selected for demonstration purposes. They are:

- I-65 (NB; between University Blvd and 1st Ave North) (0.72 miles)
- University Blvd (WB; between I-65 and US 31) (1.29 miles)
- 20th Street South (SB; between 3rd Ave South and 1st Ave North) (0.35 miles), and
- 3rd Avenue West (US 11/US78) (EB; between Center Street North and Arkadelphia Road) (0.74 miles).

Fig. 6 depicts Hourly Average Speeds (in meters per second) over a 24-h period along the four sample study corridors for baseline (no TNC) conditions as well as the three TNC service scenarios considered. It can be observed that baseline average speeds are just slightly higher than those reported from the TNC scenarios, with the exception of peak times (8:00 to 9:00 AM and 5:00 to 7:00 PM) when average speeds in the TNC scenarios were noticeably lower than the baseline scenario.

Fig. 5 Location of sample study corridors.

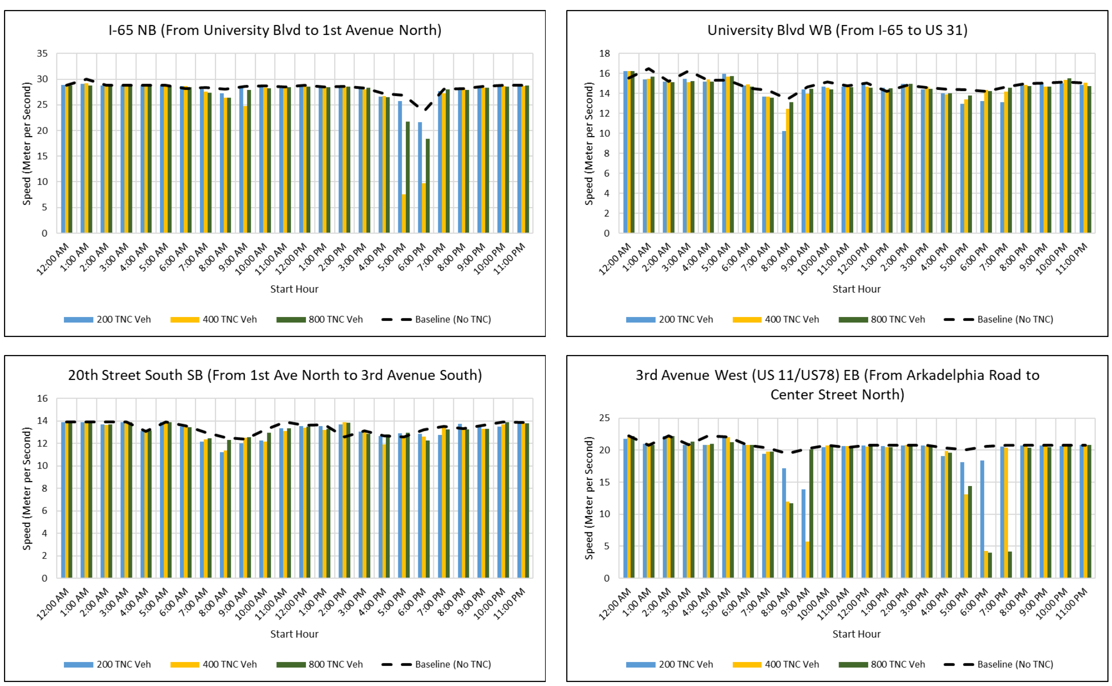

Fig. 6 Hourly average speed over 24 h for sample study corridors.

Fig. 7 illustrates Hourly Average Travel Times (in seconds) along the four sample study corridors for baseline conditions and TNC scenarios. The findings are consistent with those reported for Hourly Average Speeds. Specifically, compared to the baseline scenario, the hourly average travel times during peak hours are higher in the TNC scenarios than the baseline scenario.

Fig. 8 illustrates the Hourly Average Volume (in vehicles per hour) along the four sample study corridors for baseline conditions and TNC scenarios. When TNC vehicles are added to the network, the hourly average volume is higher than the baseline scenario in the AM/PM peak periods. This finding is in line with the hourly average speed and hourly average travel time discussed above, specifically in the peak periods, when the hourly average volume increased, the hourly average speed decreased and the hourly average travel time increased, indicating increased traffic congestion.

Fig. 7 Hourly average travel time over 24 h for sample study corridors.

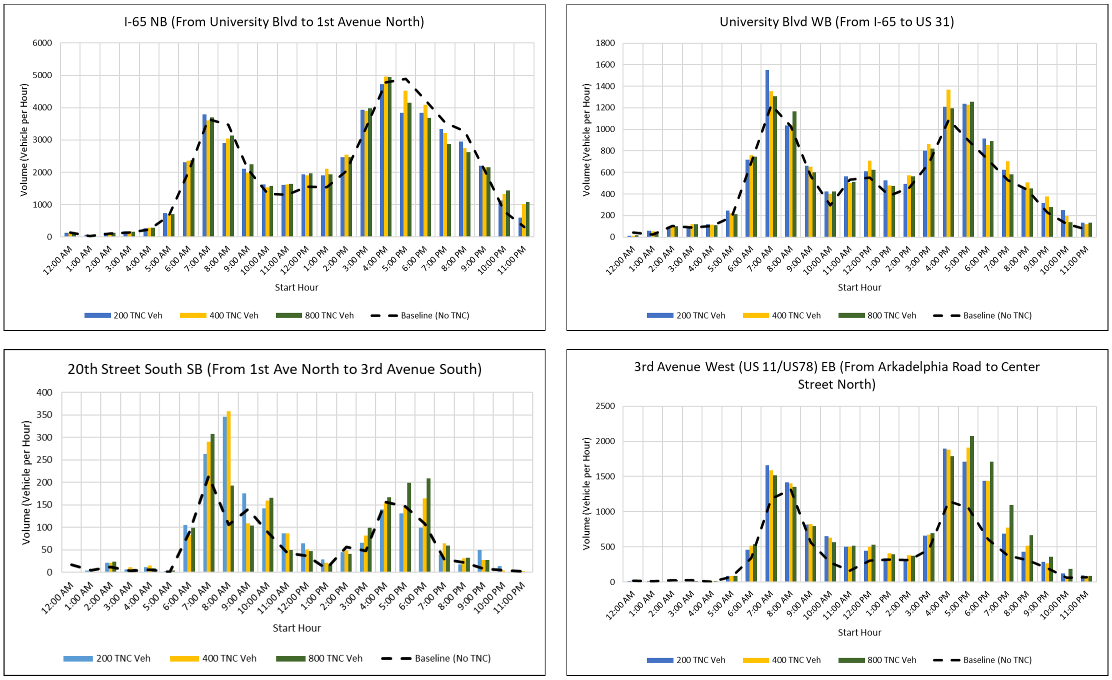

Fig. 8 Hourly average volume over 24 h for sample study corridors.

Conclusions and Recommendations

This paper examined the impact of TNC services on traffic operations in the Birmingham, Alabama metro area, a medium sized city in the southeastern US. Using the MATSim simulation platform, a baseline scenario (no TNC vehicles) and three TNC scenarios were simulated. The latter represented the operation of a TNC fleet of 200, 400, and 800 vehicles. The impacts of various TNC fleets on traffic operations were quantified using a variety of MOEs including VKT, speed, travel time, and volume. Network wide VKTs were obtained from the MATSim's output for each scenario and used to document performance impacts of TNC presence on the Birmingham network for the entire study network over a 24-h period. Hourly VKTs were also obtained and used to identify time periods during the 24-h study period when TNC impacts on traffic congestion are the greatest. Localized impacts of TNC operation on local congestion were also examined by inspection of average hourly speed, travel time, and volume data obtained from the MATSim simulation runs for selected study corridors over a 24-h period.

According to the study results, TNC scenarios increase the network wide VKT by up to 23.6% as compared to the baseline scenario. It should be noted that the VKT for the 800 TNC vehicle scenario is slightly lower (0.4%) than that of the 400 TNC vehicle scenario. One possible explanation is that the TNC demand has peaked between 400 and 800 TNC vehicles, and the stay/idle vehicle percentage is higher in the 800 TNC vehicle scenario than in the 400 TNC vehicle scenario, as it is visually evident from Fig. 3. Furthermore, the study findings show that TNCs contribute to traffic congestion, especially during AM/PM peak periods. It is evident from Fig. 4 that the hourly total VKT values increased more sharply between 7-8 AM and 4-7 PM for all TNC scenarios considered. The study further revealed that when TNC vehicles are added to the network, the hourly average volumes and hourly average travel times increase while the average hourly speeds decrease, compared to the baseline scenario, and those changes are more pronounced during AM/PM peak times as shown in Figs. 6-8. While results vary from location to location as expected, the general trends of the MOEs described above are observed at the majority of study corridors.

In addition to quantifying the impact on TNC services on traffic congestion, the study findings indicated that the optimal TNC fleet size for the Birmingham region is 400 to 500 active TNC vehicles per day. Such fleet size is adequate to serve the current demand for ride hailing services in the study area while minimizing idle time and the number of TNC vehicles hovering while waiting for TNC customer requests.

This study considered ride hailing TNC services where each customer reserved one TNC vehicle for their trip. This reflects accurately the TNC service operation in the study area, where ride pooling services are not available. In follow up work, the authors plan to investigate the effect that ride pooling (such as Uber Pool and Lyft Line) can have on traffic operations in Birmingham, Alabama.

Overall, the study findings provide valuable insights on TNC impacts on traffic congestion in the study area and medium sized cities like Birmingham and help local authorities and TNC service providers to optimize TNC operations and better serve the needs of the traveling public.

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CHAPTER 3:

OPERATIONAL IMPACTS OF VARIOUS RIDE-POOLING SERVICE OPTIONS IN BIRMINGHAM, AL

by

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Abstract

Transportation Network Companies (TNCs) use online-enabled apps to provide on-demand transportation services. TNCs facilitate travelers to connect with drivers that can offer them rides for compensation using driver-owned vehicles. The ride requests can be for (a) individual or (b) shared rides. The latter, also known as ride-pooling services, accommodates requests of unrelated parties with origins and destinations along the same route who agree to share the same vehicle, usually at a discounted fare. Uber and Lyft offer ride-pooling services in select markets. Compared to individual ride requests, ride-pooling services hold better promise toward easing urban congestion by reducing the number of automobiles on the road. However, their impact on traffic operations is still not fully understood. Using Birmingham, AL as a case study, this research evaluated the impact that ride-pooling services have on traffic operations using a Multi-Agent Transport Simulation (MATSim) model of the Birmingham metro area. Scenarios were developed to simulate baseline conditions (no TNC service) and ride-pooling availability with two types of ride-pooling services, namely door-to-door (d2d) and stop-based (sB) service and three fleet sizes (200, 400, and 800 vehicles). The results indicate that when TNC vehicles are added to the network, the Vehicle Kilometers Traveled (VKT) decrease by up to 5.78% for the door-to-door (d2d) service, and up to 2.71% for stop-based (sB) services, as compared to the baseline scenario (no TNC service). The findings also suggest that an increase in the size of the ride-pooling fleet results in a rise in total ride-pooling service VKT, network-wide total VKT, and detour distance. However, increasing the size of the ride-pooling fleet also results in a decrease in the ride request rejection rates, thus benefiting the customers and decreasing the vehicle empty ratio which, in turn, benefits the TNC drivers. The results further suggest that a fleet of 200 ride-pooling

vehicles can meet the current demand for service in the Birmingham region at all times, thus it is the optimal ride-pooling TNC fleet size for a medium-sized city such as Birmingham.

Introduction

A ride-pooling service is an on-demand transportation option wherein unrelated users are matched to share a ride in a single vehicle. Trips are matched according to pick-up and drop-off locations to ensure riders can travel together in the same vehicle while maintaining a reasonable travel time and delay time. In recent years, ride-pooling services have gained popularity as a ride-sourcing transportation option, as they allow more than one passenger's request to be served in one ride, thus reducing the number of vehicles on the network [1]. Transportation Network Companies (TNCs) view ride-pooling services as a way to increase ridership, reduce customer cost, and expand ridesharing options [2]. Uber and Lyft, the two most popular ride-hailing companies, offer Uber Pool and Lyft Line ride-pooling services to their customers in many cities throughout the world. According to Lo and Morseman [3], the Uber company launched the Uber Pool service in 2014 to make it easier for riders to share their trip with other travelers who are traveling in the same direction [3]. Drivers also benefit by reducing their operating costs while maximizing their revenue from shared rides. As part of an Uber Pool trip, Uber determines the best route along which multiple riders are going to be picked up [4]. In addition to offering rides at a reduced cost to customers, ride-pooling is viewed by many as a great way to reduce urban traffic congestion [1,2,5]. However, there is still a lack of clarity regarding the true impact of ride-pooling services on traffic network operations, in general, and traffic congestion in particular, due to the limited amount of research conducted on those topics. This is primarily attributed to the lack of readily available ride-pooling trip data and the limited ability of commercial simulation software to simulate TNC trips, including ride-pooling trips.

In our previous work [6–9], we addressed some of these limitations by (a) collecting TNC trip data from a survey of Uber/Lyft drivers in the Birmingham, AL region, and (b) showcasing the feasibility of modeling TNC services using the MATSim (Multi-Agent Transport Simulation) platform and the Birmingham, AL transportation network. To address the limitation of acquiring TNC trip data, the survey of Uber/Lyft drivers in the Birmingham metro area acted as a seed for generating population plans in the study area using the synthetic population technique. Uber trips were incorporated into the day plans of the Birmingham MATSim model using MATSim's Taxi extension (org.matsim.contrib.taxi). More details on this effort are available in [6]. It should be noted that our earlier examination of the impact of ride-hailing TNC services on traffic operations was limited to individual ride requests, since ride-pooling services were not available in the Birmingham region [7]. However, it is of interest to understand how availability of various types of ride-pooling TNC services can affect operations and the likely impacts that such services can have on traffic congestion in the service area.

In earlier studies, researchers [10–12] analyzed two distinct types of DRT transportation services, namely door-to-door (d2d) and stop-based (sB) [10–12]. Door-to-door service involves picking up and dropping off passengers at their preferred location, thus providing a highly convenient transportation service similar to a taxi. In contrast, a stop-based service operates by providing transportation to/from specific stops where passengers can meet and board the vehicle. These stops are typically located at frequently used destinations such as bus stops. A stop-based service may be more affordable for riders, compared to door-to-door. It is, however, necessary that passengers get to the location where the stop is located in order to meet their ride, which can be challenging and inconvenient for many riders, especially for those with mobility impairments.

This paper reports on a study that investigated and documented operational performance impacts of door-to-door and stop-based ride-pooling services operating in the Birmingham region. Building on our earlier work, we expanded the Birmingham MATSim model to introduce ride-pooling TNC services using the MATSim's Demand Responsive Transit (DRT) module. This allowed us to simulate various fleet sizes of TNCs in order to quantify the impact of ride-pooling services on urban congestion. The updated Birmingham MATSim simulation model provided an excellent test bed for running experiments as it was capable of simulating trips that involved personal vehicles, ride-pooling TNC trips, public transit trips, and walking trips, all in the same network.

Literature Review

As ride-pooling services became more prevalent over the last few years, some researchers attempted to study their impacts on transportation system operations. The results are mixed as some studies suggest congestion mitigation as a result of introduction of TNC ride-pooling services, whereas others suggest that such services lead to exacerbation of urban congestion. For example, a study conducted by Chen et al. [13] used ride-sourcing provider data and online surveys to examine ride-pooling impacts in Hangzhoo and suggested that such services result in a reduction of VKT by 58,124 VKT per day. Zhu and Mo [14] found that ride-pooling with a buffer time of 60 s led to an aggregate reduction of VKT of 8.21% in Haikou, China, compared with the traditional ride-hailing operation. Bischoff et al. [15] used a dynamic simulation approach to demonstrate that the overall number of VKTs may be reduced by between 15 and 20% in Berlin, if taxi rides are shared. Tirachini and Gomez-Lobo [16] conducted a Monte Carlo simulation study in Santiago, Chile, and concluded that while ride-hailing applications are expected to increase VKT, shared or pooled ride-hailing has the potential to decrease VKT. The authors point to the average occupancy rate of ride-hailing trips as a key parameter for VKT and suggest that an average occupancy rate of 2.9 passengers or more is needed to materialize congestion benefits.

On the other hand, some scholars argue that ride-pooling services might increase traffic congestion. For example, in their study of Demand Responsive Transit (DRT), Kagho et al. [17] found that the introduction of such a service was likely to increase overall VKT slightly in Wayne County, Michigan. Another study conducted in the same area [18] confirmed this finding and concluded that the introduction of DRT can increase the VKT by 22%. Furthermore, a study by Wu and MacKenzie [19] used 2017 US National Household Travel Survey data to examine the heterogeneous VKT effects on ride-sharing across population groups and reported an estimated net increase of 12.55 million VKT per day in the US due to ridesharing, compared to a case where all NHTS 2017 respondents are considered to be non-users of ride-sharing services. The authors further suggested that the impact of ride-hailing services on transportation network operational performance will continue to change dynamically in the future, as TNC services themselves and users' adoption practices continue to evolve over time.

Some other studies suggest that the impacts of ride-hailing applications on VKT and congestion are still inconclusive, including a study in Vancouver, Canada [20], and another one by [21] in San Francisco. Clewlow and Mishra [22] also recognize that VKT changes are unknown, and detailed information on the number of trips that ride-hailing applications are attracting from other modes (number, type, distance traveled, etc.) is needed to quantify such impacts. As Abouelela et al. [23] state, the reduction of VKT using ride-pooling services is possible, but it depends on a number of factors such as the use of suitable vehicle sizes to accommodate pooling service occupancy needs, the type of replaced modes (e.g., automobile versus walking or transit), and modes used to access and egress from the service [16,23].

Some studies investigated the impact of ride-pooling services on average travel time. For example, Li et al. [24]; Chau et al. [25]; and Fielbaum and Alonso-Mora [26] calculated the differences in travel time and detours between individual ride-hailing and ride-pooled rides, while Schwieterman and Smith [27] compared average trip times between Uber Pool and transit trips in Chicago. Leich and Bischoff [28] found that the average total travel time spent by the passengers from origin to destination was reduced by less than 2 min (3.5%) in simulated scenarios of door-to-door demand responsive services in Berlin, Germany. A summary of additional studies on ride-pooling impacts on VKT and aggregate travel time is available in [14].

To date, most studies on the impact of ride-pooling services have been conducted in cities/counties larger in population size than Birmingham metro area, which has a population of 0.89 million [29]. For instance, studies have been carried out in: Hangzhou, China [13] (8.24 million population [30]); Haikou City, China [14] (2.02 million population [30]); Berlin, Germany [15] (3.57 million population [30]); Santiago, Chile [16] (6.9 million population [30]); and Wayne County, Michigan [17,18] (1.77 million population [31]). Since the population size affects transportation demand, further research is needed to investigate how ride-pooling services affect the operational efficiency of the transportation system in medium-sized cities (population between 350,000–999,999).

The purpose of this study is to address this need by examining and documenting the impact of ride-pooling services in Birmingham, AL, a medium-sized city in the Southeast. Comparisons of measures of traffic performance (e.g., Vehicle Kilometers Traveled, travel time, and user waiting time) in the presence of door-to-door and stop-based ride-pooling services provide valuable insights on their impacts and help identify conditions under which such services yield the greatest benefits. Moreover, the study considers various fleet sizes and provides guidance on selection of a proper fleet size in order to balance the needs of the riders, drivers, and traffic network operators.

Methodology

The aim of this study was to quantify the operational performance impacts of ride-pooling services (e.g., Uber Pool and Lyft Line) in the Birmingham metro transportation network. As of the time of the study, no ride-pooling services were offered by Uber and Lyft in Birmingham. Thus, in the absence of field data, we simulated the Birmingham transportation network (a) under baseline conditions and (b) assuming the presence of ride-pooling services. The simulation outputs allowed us to obtain and compare selected performance measures, including trips by mode, VKT, detour distances, mean passenger wait- and in-vehicle travel time, among others.

Study Area

The study area is located in north central Alabama and covers Jefferson and

Shelby counties. Jefferson County encompasses an area of 1119 square miles [32], while Shelby County covers 800 square miles [33]. The population density in Jefferson County is 592 people per square mile [34], whereas in Shelby County it is 274 individuals per square mile [35]. The Birmingham–Jefferson County Transit Authority (BJCTA) operates a public transportation system, which includes buses and a paratransit service. Around 95% of Birmingham residents commute to work by driving or carpooling [36]. This corresponds to the findings of a commuter survey carried out in the Greater Birmingham region, which revealed that over 90% of transportation users use private automobiles to commute [37]. According to [36], the average individual driving distance per day within the Greater Birmingham area is approximately 34.1 miles.

Simulation Model Selection

The simulation platform used in this study was MATSim. MATSim is an open-source agent-based and activity-based microsimulation framework that is implemented as a Java application and is capable of simulating large-scale scenarios for various transportation options [38]. The model uses daily travel plans of all transportation users (population) and executes them on the road network to simulate traffic. Using a scoring mechanism and through a re-planning process, agents (transportation users) seek possibilities to optimize their plan at each iteration. The iterative process continues as long as the overall score of the population continues to increase. A detailed description of MATSim features can be found in Horni et al. [39,40].

The model selection in this study was based on MATSim's effectiveness in simulating TNC operations as demonstrated in the literature and confirmed by our earlier research efforts [7,8,38]. In particular, MATSim's Demand Responsive Transport (DRT) extension is a key software feature that gave MATSim a unique advantage over other available transportation software options considered. This extension enables the simulation of on-demand ride-pooling services [11,15,41], and makes MATSim an excellent choice for a simulation platform for meeting the objectives of our study.

Simulation Study Experimental Design

We developed the ride-pooling scenarios based on consideration of two attributes: ride-pooling service type and fleet size. Specifically, we considered two types of ride-pooling services, namely door-to-door (d2d) and stop-based (sB), and three fleet sizes (i.e., 200, 400, and 800 vehicles). The maximum acceptable waiting time was set to 5 min, as in other literature studies [15,41]. By combining the different options, 6 ride-pooling scenarios were developed for further analysis. In addition, we considered the baseline scenario where we simulated no ride-pooling operations [7] and used it to facilitate comparisons.

Birmingham MATSim Simulation Model

Every MATSim model is built around a configuration file, a network file, and a population file. The configuration file defines the parameters and settings of the model that determine how the model behaves and provides access to the settings at runtime. The network file describes the details of the nodes and links that compose the transportation network and associated attributes (e.g., node coordinates, link length, number of lanes, speed, and capacity). The population file provides information about travel demand, i.e., lists of agents (travelers) and their day plans (trips). The population file contains the list of agents. Each agent has a list of plans, and each plan contains a list of activities and legs that describe each agent's planned actions.

Building on our earlier work [6,7], we adopted the Birmingham MATSim simulation model and made necessary modifications to the model to meet the needs of the current study. More specifically, in our previous research, we utilized MATSim's Taxi extension to simulate individual ride requests using the Birmingham MATSim model. In the current study, we adopted MATSim's Demand Responsive Transport (DRT) extension to simulate on-demand ride-pooling services in the Birmingham network. This extension provides the ability to fit multiple trip requests within a single TNC vehicle, a critical requirement for meeting the objectives of our study.

MATSim input files for the Birmingham model (e.g., network file, plans file, vehicles file, transit schedule file, and transit vehicles file) were adopted from [6] and allowed for multi-modal simulation of traffic operations in the Birmingham network (including generation of trips by passenger car, transit bus, and walking). We also added the stops file for the stop-based (sB) scenario. The stops file was created based on existing bus stops in the study area and included a total of 1856 bus stops which were geocoded as an XML input file.

The DRT MATSim extension was used to simulate ride-pooling trips for the study door-to-door (d2d) and stop-based (sB) scenarios. The DRT module allows the simulation of pooled rides in MATSim with one or several DRT operators, each of them having its own characteristics, such as the vehicle fleet, detour, or scoring parameters. For the purposes of maintaining a realistic comparison with the baseline scenario in [7], the configuration file in our study used identical parameters with those in our earlier work [6,7]. The DRT module configuration file, created specifically for this study, defined the

DRT operational characteristics and selected reasonable parameter threshold values based on recommendations from earlier studies and local considerations. For example, studies conducted in Germany [10,11,41,42] used a 30 s stop time duration for pickup and drop off of passengers, Bischoff et al. [43] assumed a stop duration of 60 s, and a study conducted by [17] in Wayne County, Michigan, set the stop duration to 105 s. In our study, we set a stop time duration of 60 s for passengers being picked up and dropped off at each stop. The maximum number of passengers per vehicle was set to 4 and the maximum detour time in our study was 8 min.

In order to improve the computational efficiency of the simulation and in accordance with earlier studies that used MATSim to simulate city-level transportation networks, 10% of the total population in Birmingham was used as input [6,9,40,44]. Thus, plans were executed using a population size of 69,826. MATSim generates output data that can be used to analyze results, as well as to monitor the simulation setup progress. A link stats file containing hourly count values and travel times on every network link is produced in each iteration, and network wide measures of effectiveness (MOEs) can be obtained. In our study, we evaluated the Birmingham network performance under the six study ride-pooling scenarios using vehicle kilometers traveled (VKT) and compared with baseline conditions (no TNC presence). We also considered mode shifts toward the ride-pooling service and their impacts on network operations. The results are summarized next.

Results

Status of Ride-pooling Vehicles

Figure 1 depicts the number and status of ride-pooling d2d and sB service vehicles by hour of day (24-h total) assuming different fleet sizes (200, 400, and 800 ride-pooling vehicles). In Figure 1 the status of ride-pooling vehicles, i.e., en-route (requested but not completed), departing, and arriving, during each hour of the day is clearly marked by green, red, and blue lines, respectively. We can observe that the number of ride-pooling vehicles en-route to pick up customers increases as the number of TNC vehicles increases (from 200 to 400 and 800), and peaks during the a.m. and p.m. peak traffic periods. According to Figure 1, there are more vehicles en-route for d2d compared to those in the sB scenario when 800 vehicles are added to the network. However, this reversal in the trend can be explained by the total number of ride-pooling trips, which can be seen in Table 1. When 800 TNC vehicles were added to the network, the d2d service had a higher number of ride-pooling trips than sB. In contrast, sB trips increased by approximately 7.6%, which indicates that the demand for sB service is nearing the saturation point.

Vehicle Occupancy Profiles

Figure 2 illustrates vehicle occupancy profiles for d2d and sB ride-pooling services under various fleet sizes considered. Color codes indicate whether a TNC vehicle is a stay (gray color), carries zero passengers (purple), carries one passenger (yellow), or accommodates two passengers (green), three passengers (blue), or four passengers (red) as a ride-pool. During the stay period, a vehicle is either parked or idle and waiting for the next trip request to be made. According to Zwick and Axhausen [45], if the status of the TNC vehicle is zero passengers, the TNC vehicle is either rebalancing or is on its way to pick up a rider.

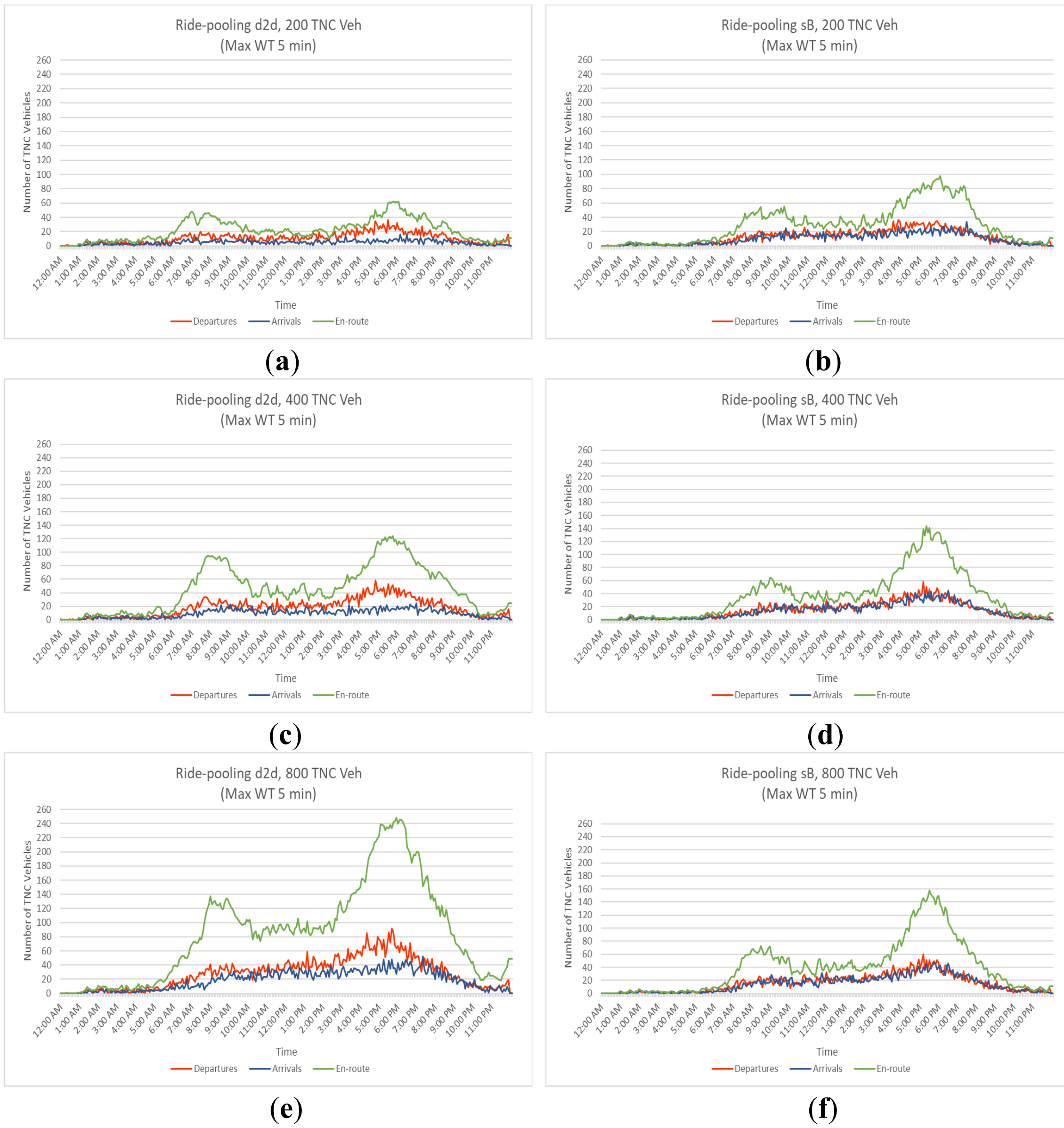


Figure 1. Ride-pooling Vehicle Status by Hour of Day for Various Fleet Sizes. (a) ride-pooling (d2d) 200 TNC Veh; (b) ride-pooling (sB) 200 TNC Veh; (c) ride-pooling (d2d) 400 TNC Veh; (d) ride-pooling (sB) 400 TNC Veh; (e) ride-pooling (d2d) 800 TNC Veh; (f) ride-pooling (sB) 800 TNC Veh.

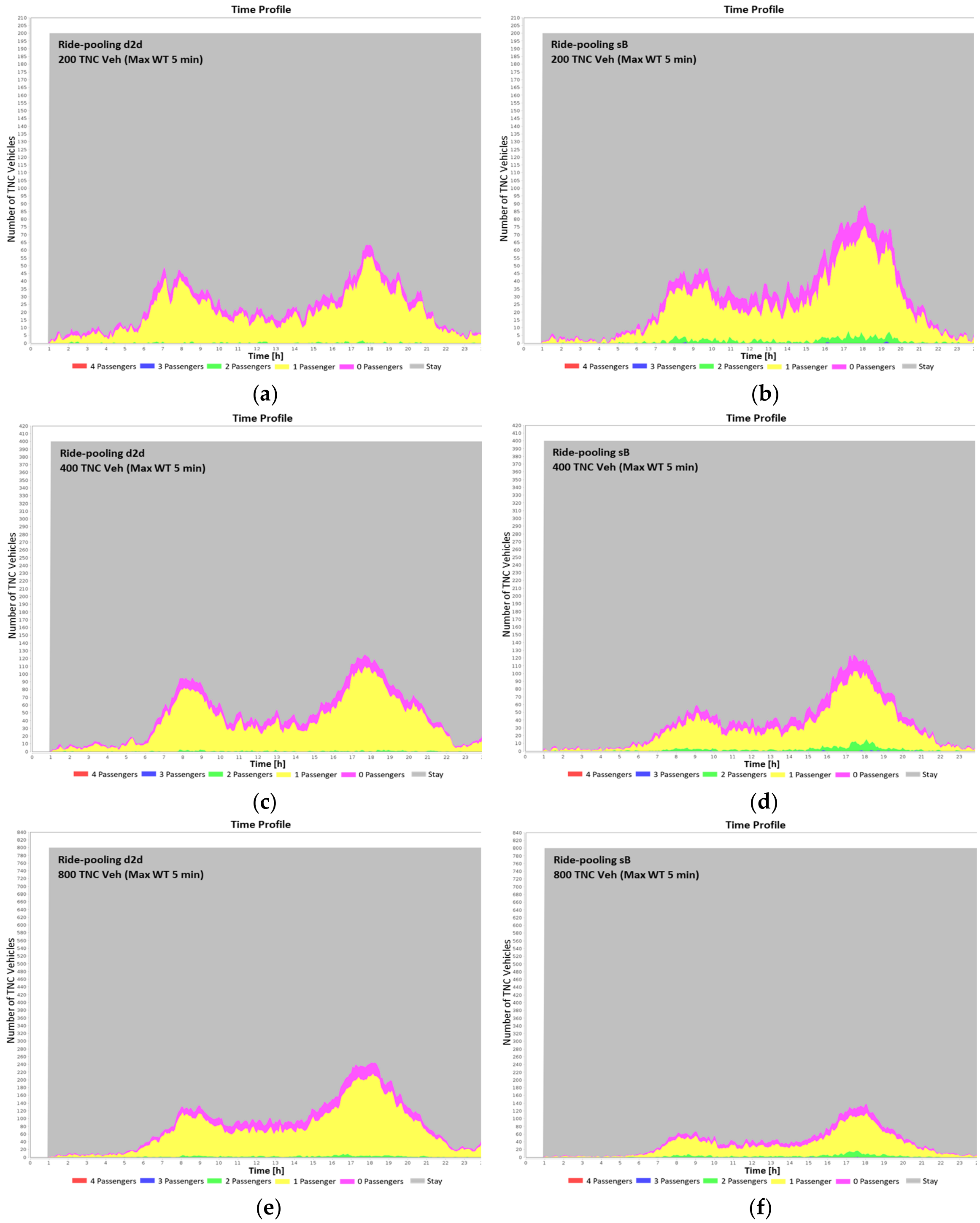


Figure 2. Vehicle Occupancy Profiles for Various Fleet Sizes. (a) ride-pooling (d2d) 200 TNC Veh; (b) ride-pooling (sB) 200 TNC Veh; (c) ride-pooling (d2d) 400 TNC Veh; (d) ride-pooling (sB) 400 TNC Veh; (e) ride-pooling (d2d) 800 TNC Veh; (f) ride-pooling (sB) 800 TNC Veh.

In all study scenarios, we can observe that ride-pooling vehicles at stay (gray color) are overrepresented, meaning that the demand for ride-pooling services in the Birmingham region is below the available supply for service. This is the case even during the a.m. and p.m. peak periods. The results show that even a fleet of 200 ride-pooling vehicles can comfortably meet the current demand for service in the Birmingham region at all times. Figure 2 also shows that the vast majority of passenger-carrying TNC vehicles are single-passenger rides (yellow) and neither the d2d service nor the sB service serve any trip requests from more than three passengers in a single ride. Thus, vehicles that can accommodate three passengers meet the service needs of the Birmingham area and can be used as ride-pooling vehicles. Although Figure 2 indicates that most car-pooling trips in our study were single-passenger trips, it can still be concluded that the introduction of ride-pooling has a positive impact on the traffic network operation. This is due to two main reasons: (a) an observed mode shift from automobile use to transit, walking, and ride-pooling, and (b) a reduction in the total number of vehicular trips (combining both private auto and ride-pooling) for both d2d and sB ride-pooling services, as demonstrated in Table 1.

Impact of Ride-pooling Service Availability on Modal Choice

Table 1 summarizes the distribution of trips by mode for the baseline and the six ride-pooling service scenarios analyzed in this study, under baseline conditions, at total of 144,014 vehicle trips were performed (all by a private automobile). However, when TNCs were introduced, the total number of vehicle trips (private automobile and ride-pooling combined) decreased in all ride-pooling scenarios considered. This represents a decrease in the range of 5.45% to 2.81% compared to the baseline (or 136,163 to 139,974 compared to 144,014 vehicle trips). The results in Table 1 also show that as the TNC fleet size increases, the number of ride-pooling trips increases as well. It is worth noting that the changes are more pronounced under d2d scenarios versus sB scenarios. Specifically, as the TNC fleet size changes from 200 to 400 and 800 vehicles, the number of ride-pooling trips almost doubles under d2d scenarios, while the number of ride-pooling trips under sB scenarios increases at a lower pace. Ride-pooling scenarios also show more transit/walk trips than those of the baseline scenario, however, increase in ride-pooling fleet sizes reduces the shift toward transit/walking modes.

Table 1

Statistics of Executed Plans-Trips by Mode (Max Acceptable Wait Time: 5 min).

TNC Fleet Size (Vehicles)	Scenario	Transit Trips (Total Ridership)	Walk Trips	Private Auto Trips	Ride-pooling Trips	Vehicle Trips (Private Auto + Ride-pooling)	Change in Vehicle Trips due to Ride-pooling (Baseline – Number of Vehicle Trips)	% Change in Vehicle Trips due to Ride-pooling compared to Baseline
0 TNCs	Baseline	2,648	5,172	144,014	0	144,014	0	0%
200 TNCs	d2d	4,590	8,115	135,156	1,386	136,542	-7,472	-5.19%
	sB	3,649	7,987	136,167	2,909	139,076	-4,938	-3.43%
400 TNCs	d2d	4,359	7,693	133,445	2,718	136,163	-7,851	-5.45%
	sB	3,423	7,840	135,914	3,853	139,767	-4,247	-2.95%
800 TNCs	d2d	3,919	7,093	131,333	5,420	136,753	-7,261	-5.04%
	sB	3,272	7,851	135,828	4,146	139,974	-4,040	-2.81%

Impact of Ride-pooling Service Availability on Network-wide Operations

Total Daily Network VKT

Using Equation (1) below, we calculated the total daily VKT in the Birmingham network for each of the six ride-pooling scenarios in our study. The results are summarized in Table 2.

$$VKT_{Day} = \sum_{h=0}^{h=23} Vehicle\ Count\ /Hour\ x\ \frac{Link\ Length\ (m)}{1000\ \frac{m}{km}} \quad (1)$$

It can be observed that ride-pooling services scenarios show a reduction in the total VKT, when compared to the baseline scenario. As shown in Table 2, ride-pooling d2d scenarios result in a reduction in total daily VKT of up to 5.78% (or up to 131,070 fewer VKT) in comparison to the baseline scenario, while sB scenarios show more moderate improvements (up to 2.71% or 61,424 VKT reduction over the baseline). We can also see that under all ride-pooling scenarios, a TNC fleet size of 200 vehicles yields the best VKT results and larger fleet sizes result in an increase in the total daily VKT.

Further analysis indicates that the total hourly VKT in the presence of ride-pooling services peaked during the a.m. and p.m. traffic peak periods (7 to 8 a.m. and 4 to 5 p.m.), however, it remained below that of the baseline as illustrated in Figure 3. The afternoon peak hours experienced the highest total hourly VKT values reported throughout the day. It is worth noting that the difference in VKT among scenarios tends to be relatively small, but, overall, smaller fleet sizes result in lower total hourly VKT, an observation that is consistent with the total VKT results reported earlier.

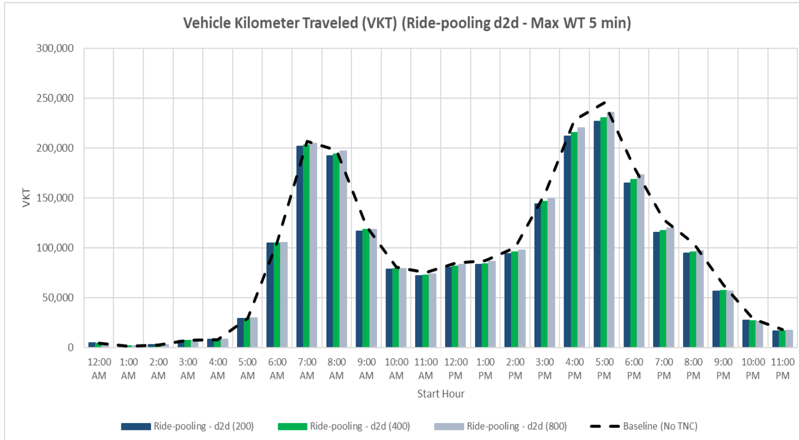
Table 2

Total Daily VKT under Various Scenarios (Max Acceptable Wait Time: 5 Min).

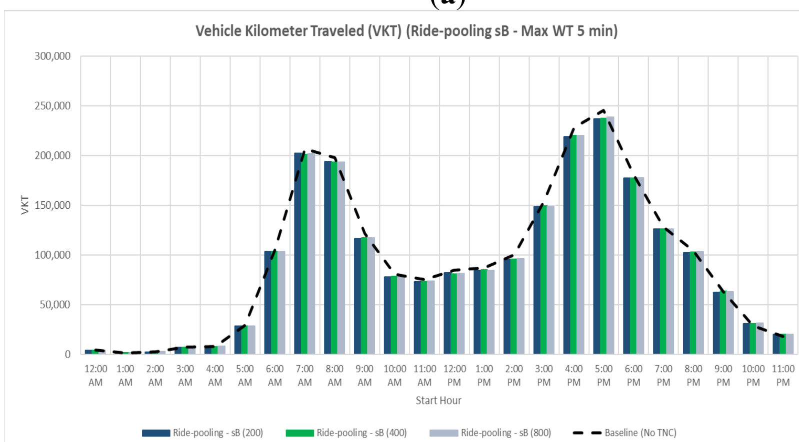
TNC Fleet Size (Vehicles)	Scenario	Total Daily VKT	Change in Total Daily VKT (Baseline – Ride-pooling Scenario)	VKT % Diff. to Baseline
0 TNCs	Baseline	2,265,716	---	---
200 TNCs	d2d	2,134,646	-131,070	-5.78%
	sB	2,204,292	-61,424	-2.71%
400 TNCs	d2d	2,157,837	-107,879	-4.76%
	sB	2,209,273	-56,443	-2.49%
800 TNCs	d2d	2,193,750	-71,966	-3.18%
	sB	2,212,335	-53,381	-2.36%

Ride-Pooling Daily VKT

Figure 4 illustrates the daily VKT for ride-pooling trips in the Birmingham region for two ride-pooling service types (d2d and sB) and for three fleet sizes (200, 400, 800 available ride-pooling vehicles). As shown in Figure 4, an increase in the size of the TNC fleet results in an increase in the ride-pooling total daily VKT for both the d2d and sB scenarios. It is also observed that the d2d service generates a greater number of VKT than the sB, as the fleet size increases from 200 to 400 and 800 vehicles. This can be attributed to the longer mean travel distance associated with d2d compared to sB. Additionally, sB service vehicles only pick up and drop off passengers at designated locations within the study area, thus covering a shorter range of service. However, d2d service vehicles can pick up and drop off passengers from anywhere within the network, and cover service requests from across the entire service area. The results confirm that the sB ride-pooling service is more desirable from the operators' perspective, as it results in lower VKT, even though it is often less desirable from the perspective of the user that typically favors d2d services due to the added convenience.

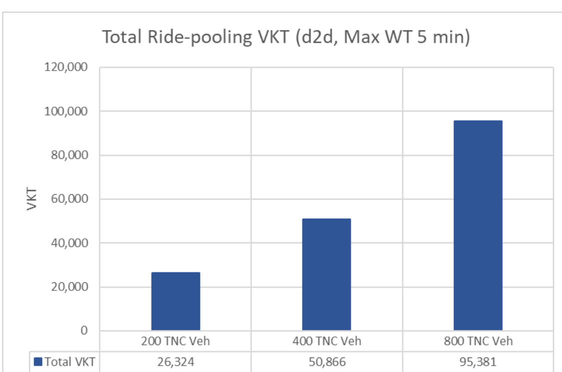


(a)

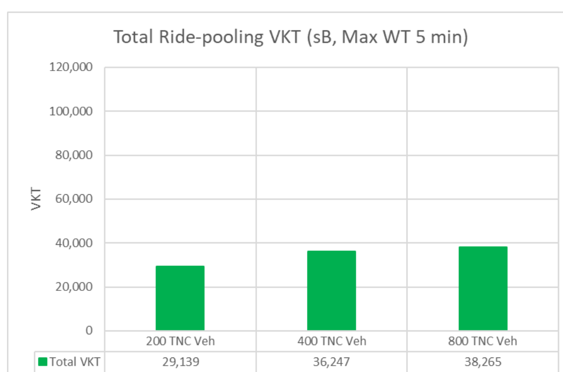


(b)

Figure 3. Hourly Distribution of Total VKT under Various Scenarios. (a) ride-pooling (d2d); (b) ride-pooling (sB).



(a)



(b)

Figure 4. Total VKT for Ride-pooling Trips under Various Scenarios. (a) ride-pooling (d2d); (b) ride-pooling (sB).

Ride-pooling Vehicle Distance Travelled

Table 3 reports daily distance traveled by ride-pooling vehicles in the Birmingham network under the assumption of max acceptable wait time of 5 min for two types of operations (d2d and sB service), and three fleet sizes (200, 400, and 800 vehicles). The daily distance that the ride-pooling vehicles cover while empty is also reported and used to calculate the empty ratio. Empty ratio refers to the ratio of travel distance covered by ride-pooling vehicles with no passenger on board over the total travel distance covered by TNC vehicles.

Table 3

Daily Distance Traveled by Ride-pooling Vehicles (Max Acceptable Wait Time: 5 Min).

TNC Fleet Size (Vehicles)	Scenario	Total Daily Distance Traveled (km)	Daily Distance Traveled while Empty (km)	Empty Ratio (%)	Total Detour Distance (km)
200 TNC Veh	d2d	26,324	2,145	8.15%	1,395
	sB	29,139	3,248	11.15%	2,974
400 TNC Veh	d2d	50,866	4,132	8.12%	2,743
	sB	36,247	3,518	9.71%	3,948
800 TNC Veh	d2d	95,381	7,354	7.71%	5,492
	sB	38,265	3,455	9.03%	4,250

From Table 3, it is evident that the daily distance traveled while empty increased as the TNC fleet size increased in size. Additionally, there was a corresponding decrease in the empty ratio as the size of the TNC fleet increased. This trend can be attributed to mode shifts that resulted in an increase in ride-pooling demand, which occurs with an increase in TNC fleet size. Table 1 indicates that the number of TNC trip demands increased as the TNC fleet size increased, while the ride request rejection rate decreased as shown in Table 4 below. These findings align with earlier research, which demonstrated a decrease in the proportion of empty vehicles on the road when the DRT fleet size increased, resulting in more vehicles distributed in the network [17]. Furthermore, the empty ratios were higher under the assumption of sB operations, compared to d2d service. The sB service also resulted in higher total detour distance, compared to the d2d service for fleet sizes of 200 and 400 TNC vehicles.

Customer Service Time and Ride Request Rejection Rate

Table 4 summarizes simulated average customer wait times, in-vehicle travel times, mean passenger service times, and ride request rejection rates for all study scenarios. Mean passenger service times are calculated as the sum of average customer wait times, and average in-vehicle travel times. The results show that the d2d ride-pooling service led to higher average customer wait times and higher in-vehicle travel times, compared to the sB service. As a result, the total customer service time for the d2d service was consistently greater than that of the sB service when accounting for fleet size. According to the results in Table 4, the average passenger wait time for ride-pooling d2d scenarios was up to 3.7 min (3 min for ride-pooling sB scenarios).

Table 4

Ride-pooling Customer Service Time and Ride Request Rejection Rate for Various Scenarios (Max Acceptable Wait Time: 5 Min).

TNC Fleet Size (Vehicles)	Scenario	Mean Passenger Wait Time (s)	Mean in-Vehicle Travel Time (IVTT) (s)	Mean Passenger Service time (s)	Mean Travel Distance (m)	Ride Request Rejection Rate (%)
200 TNC Veh	d2d	219	1,153	1,372	17,486	55%
	sB	182	703	885	9,415	18%
400 TNC Veh	d2d	220	1,195	1,415	17,271	47%
	sB	164	669	833	9,050	10%
800 TNC Veh	d2d	214	1,132	1,346	16,485	33%
	sB	163	676	839	9,011	8%

According to Table 4, as the TNC fleet size increases for both d2d and sB ride-pooling services, the mean travel distance decreases. This phenomenon can be attributed to the increased availability of TNC vehicles, making it more convenient to match passengers with nearby drivers. This, in turn, could encourage individuals to utilize the TNC service more frequently, particularly for shorter distances.

The ride request rejection rate was determined by dividing the number of rejected trips by the total requested number of pooled rides. The ride request rejection rate for d2d ride-pooling scenarios reached up to 55% for TNC fleet size of 200 vehicles, while the rejection rate for sB ride-pooling scenarios was considerably lower (up to 18%). The results in Table 4 further confirm that an increase in the TNC fleet size results in a reduction in ride request rejection rates. For example, when the TNC fleet size increases from 200 to 800 vehicles, the rejection rate falls from 55% to 33% for d2d ride-pooling services, and from 18% to 8% for sB ride-pooling services.

Summary and Conclusions

This study aimed at assessing how ride-pooling services affect traffic operations throughout the Birmingham, AL metro area. Using the MATSim simulation platform, a baseline scenario (no TNC vehicles) was simulated for the Birmingham network [6,7], along with six ride-pooling scenarios that represented two variations in the ride-pooling service type (d2d and sB) and three TNC fleet sizes (200, 400, and 800 vehicles). The ride-pooling scenarios were simulated using MATSim's DRT extension and assumed a maximum acceptable waiting time of 5 min. Trips for transit, walk, private automobile, and ride-pooling travel modes were obtained from each simulated scenario and compared to the baseline in order to determine modal shifts in the presence of TNC ride-pooling services. The VKT for each scenario was obtained from the DRT output of MATSim and used to quantify the impacts of the ride-pooling service on network operations across the Birmingham network over a period of 24 h. In addition, consideration of the TNC vehicle status over a 24-h period for each study provided useful information to the TNC operator about the operational efficiency of ride-pooling options for various TNC fleet sizes. Last, but not least, ride-pooling customer service time and ride request rejection rates were evaluated to gain insights on the quality of customer service offered by ride-pooling services under various study scenarios.

Our results showed that the introduction of ride-pooling TNC services in the Birmingham region can be beneficial from a network operation perspective, as it has the potential to reduce VKT by up to 5.78% for d2d services, and up to 2.71% for sB services, compared to the baseline scenario (no TNC service). These results are consistent with findings from studies involving larger cities [13–16] that reported that an 8–20% reduction in VKT is possible in the presence of ride-pooling services.

When comparing the simulated VKT from this study to our earlier research findings in [7], we can clearly see the effectiveness of ride-pooling services. For the same baseline traffic network, similar demand conditions, and for a fleet of 200 TNC vehicles, ride-pooling d2d TNC services reduce VKT by 5.78% in the Birmingham network, whereas individual ride TNC requests increase VKT by 22% [7], compared to the baseline scenario. Similar conclusions can be drawn from the comparison of different fleet sizes and the comparison between sB and individual ride TNC services, and are in agreement with findings reported by Tirachini and Gomez-Lobo [16] from a simulation study in Santiago, Chile. Thus, it is recommended that TNC companies operating in the

Birmingham region consider expanding their services to provide car-pooling services, in addition to individual TNC rides, given the anticipating benefits to the transportation network performance from the operation of ride-pooling TNC services.

The study concludes that an increase in the TNC fleet size leads to a decrease in the vehicle-empty ratio for both d2d and sB ride-pooling services. However, the total daily distance traveled by ride-pooling vehicles increases with an increase in the TNC fleet size for both d2d and sB services. The most significant increase in the total daily stance traveled occurred for d2d, with an increase of up to 93.2% (from 26,324 km to 50,866 km) when the fleet size increased from 200 to 400 TNC vehicles. Additionally, the study found an increase of up to 24.4% (from 29,136 km to 36,247 km) for sB when the fleet size increased from 200 to 400 TNC vehicles. The observed trend can be explained by the shift in transportation modes from automobile trips to ride-pooling services. This shift results in an increase in demand for ride-pooling services, which is seen with an increase in the TNC fleet size.

The study findings also show that customer service time is almost insensitive to changes in the size of the TNC fleet for both ride-pooling services considered (i.e., d2d and sB). This observation is consistent with earlier studies, including [43], which also found that an increase in the TNC fleet size had a minimal or no effect on the in-vehicle travel time for both d2d and sB ride-pooling services. When comparing the two service options, our results suggest that the sB ride-pooling service was the most effective ride-pooling option, as it resulted in lower average customer service times when compared to the d2d service.

The study found that with an increase in the size of the TNC fleet, both d2d and sB services experienced a reduction in mean travel distance. The most significant decrease in the mean travel distance occurred for d2d, with a reduction of up to 4.55% (from 17,271 m to 16,485 m) when the fleet size increased from 400 to 800 TNC vehicles. Additionally, the study results showed a decrease of up to 3.88% (from 9415 m to 9050 m) for sB when the fleet size increased from 200 to 400 TNC vehicles.

The study findings further confirm that ride request rejection rates fall as the TNC fleet size increases. For instance, for sB service, the ride rejection rate fell from 18% to 10% (a 44% reduction) when the TNC fleet size increased from 200 to 400 vehicles. A further 20% reduction was observed when the fleet size increased from 400 to 800 vehicles. These findings are consistent with results from a previous study [18], which reported that increasing the DRT fleet size from 150 to 250 vehicles resulted in a 36% decrease in rejection rates and a 28% reduction in the rejection rate when the DRT fleet size was increased from 250 to 350 vehicles [18]. It should be noted that the Birmingham simulation study assumed a maximum acceptable wait time of 5 min. This resulted in high ride request rejection rates, especially when TNC fleet sizes were low. Higher acceptable wait times (e.g., 10 min) are expected to reduce the ride request rejection rates and are recommended for consideration in follow-up studies.

Overall, this study contributes to a better understanding of how ride-pooling services impact traffic congestion in medium-sized cities such as Birmingham, AL. Moreover, the findings from this study can guide TNC providers and transportation authorities in their efforts to enhance TNC operations in medium-sized cities with similar characteristics and better serve the needs of transportation users in these regions.

Study Limitations

In this study, we are addressing a critical limitation in the literature, i.e., examining impacts of ride-pooling services on traffic operations in a medium-sized city. However, given that travel behaviors and local conditions vary from city to city, the findings of the study are only generalizable to settings that are similar to the city of Birmingham. Additional studies are recommended in other medium-sized metro areas across the US in the future to further expand the knowledge and understanding of the relationship between TNC service availability and traffic congestion. Due to difficulties in obtaining TNC trip data directly from Uber and Lyft for the Birmingham region, the study relied on local Uber drivers to extract trip records from their logs, which may not be representative of the entire TNC population. Furthermore, the use of a synthetic population to generate travel plans for all travelers in the network is a limitation in MATSim, as a synthetic population may not accurately reflect the travel behaviors of transportation users, including TNC users in their entirety [6,7]. However, this study still provided proof of the feasibility of modeling TNC services on the same simulation platform with automobile, transit, and walking trips using MATSim, thus confirming its superiority over other traffic simulation platforms toward modeling multimodal operations, including ride-pooling TNC services.

A significant amount of knowledge can be gained from the analysis of TNC data, such as user behavior and travel patterns. Thus, this study further recommends considering such data in the estimation of mode choices and mode shifts. One challenge, noted earlier, is the difficulty of obtaining empirical data from TNCs, as such data are closely guarded by TNC providers [46]. However, some recent initiatives demonstrate promise toward data sharing between TNC providers and public agencies. One notable example is that of the State of California that requires TNC providers to submit Annual Reports Data. Such reports are made publicly available by the California Public Utilities Commission at a dedicated TNC Data Portal [47] after they have been redacted to remove any identifiable information. More wide-spread sharing of data between TNC companies and researchers is encouraged in the future and is expected to lead to a better representation of TNC trips in transportation modeling, and a more in-depth understanding of mode choices and modal shifts in markets where TNCs operate. This, in turn, can benefit transportation agencies and TNC providers as well, and assist them to better serve the needs of the traveling public.

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CONCLUSIONS

The findings reported in this dissertation examined the issue of on-demand ridesourcing services' impact on traffic operations in a medium-sized city. The comprehensive literature review and research case studies extensively covered shared mobility transportation options, including their service types, potential impacts, data acquisition limitations, and simulation platforms available. The large-scale simulation study of TNC services addressed the potential impacts on networkwide operations and the operational performance on specific corridors within the Birmingham metro area. Furthermore, the analysis of simulation model results highlighted the significance of utilizing simulation modeling approaches to simulate the impact of TNCs due to the limited availability of TNC data and challenges in obtaining travelers' diaries in the study area. The findings of each of these studies are summarized below.

The literature review and research case studies in Chapter 1 act as a reference tool for researchers and practitioners, allowing them to gain a deeper understanding of the simulation models available for simulating shared modes, including their limitations, capabilities, simulated modes, input prerequisites, and model outputs. The attributes of each simulation model were reviewed and documented. The study found three simulation tools that exhibit the potential for simulating shared modes trips. The comparative analysis of the three available simulation software revealed that the Multi-Agent Transport Simulation (MATSim) tool is a highly promising platform for simulating shared mobility trips. The literature review and research case studies exposed the advantages and disadvantages associated with each simulation model, which need to be carefully considered before one selects a simulation model to use in a research project.

Chapter 2 focused on exploring the possible effects of TNCs' individual trip requests on traffic operations in the Birmingham, AL metro area. A comprehensive model that encompasses Uber/Lyft trips, was developed in order to quantify the impact of on-demand ridesourcing services for various sizes of TNC fleets. This study simulated four scenarios, including the baseline scenario with no TNC vehicles, as well as scenarios with TNC fleet sizes of 200, 400, and 800 vehicles using the MATSim simulation tool. Various measures of effectiveness (MOEs), such as VKT, speed, travel time, and volume, were employed to evaluate the impact of on-demand ridesourcing trips. The simulation study results indicated that, in the three scenarios where TNC vehicles were added to the network, TNC services led to an increase in networkwide VKT compared to the baseline scenario where no TNC vehicles were included. There was a maximum increase of 23.6% in the networkwide VKT when compared to the baseline scenario. However, increasing the number of TNC vehicles from 400 to 800 only resulted in a 0.4% increase in the networkwide VKT, which could be attributed to meeting the demand for service. During the AM/PM peak periods, the simulation study results showed that in scenarios where TNC vehicles were added to the network, there was an increase in travel time and volume, and a decrease in speed at the selected network locations, as compared to the baseline scenario. The study's findings revealed that in Birmingham, AL, about 400 to 500 TNC vehicles per day are enough to fulfill the current demand, which will help to reduce vehicle idle time and reduce the number of TNC vehicles circling the network in search of trip requests.

Chapter 3 presented an analysis of the effects of ride-pooling services in

Birmingham, AL. The study examined 6 ride-pooling scenarios, with 3 being door-to-door (d2d) services and 3 being stop-based (sB) services. The analysis involved the addition of 200, 400, and 800 TNC vehicles to the network for each of the d2d and sB services, and the results are compared to the baseline scenario from Chapter 2, where no TNC vehicles are added to the network. The MATSim DRT extension was employed to model d2d and sB scenarios, with a maximum acceptable passenger waiting time of 5 minutes. Based on the results, ride-pooling services have the potential to decrease VKT by up to 5.78% for d2d service and up to 2.71% for sB service compared to the baseline scenario without TNC service. The study concludes that changes in TNC fleet size for the d2d and sB ride-pooling services do not significantly affect passenger service time. When comparing the two carpooling options, the study found that sB ride-pooling service is more effective than d2d in terms of average passenger service times, as it resulted in shorter average passenger service times. The study's results verify that as the TNC fleet size increases, the ride request rejection rates decrease.

As a result of the research carried out for this dissertation and documented in Chapters 1 through 3, a valuable understanding has been developed regarding the simulation of TNC services in Birmingham, AL. The research demonstrates the feasibility of using the MATSim large-scale traffic simulation model and adopting two of its extensions in order to accommodate TNCs services as a travel mode option. This research addressed the research gap related to the impact of TNC services in a medium-sized city. Research results indicate that ride-pooling services are more efficient than individual rides from TNCs, particularly when it comes to reducing VKT. It is therefore recommended that TNCs operating in the Birmingham metro area expand their services to include a ride-pooling option alongside individual TNC rides. The anticipated benefits to the transportation network performance from the implementation of TNC ride-pooling services make this expansion an important factor to consider. Moreover, the study offers valuable recommendations on optimal fleet size for the current demand for TNC services in the Birmingham region.

It is recommended to expand this research by studying the impact of dynamic price changes (such as surge/prime time) on TNC services. The pricing strategy of TNCs responds to changes in supply and demand, and surge pricing is one way of managing high-demand periods. It may, however, encourage drivers to seek out surge areas to boost their earnings, leading to traffic congestion and longer wait times for riders. Additionally, customers may avoid requesting rides in surge pricing areas due to the higher prices, which can lead drivers to hover the network empty in an effort to receive a trip request from the inside or outside the surge area. It is, therefore, important to study the impact of surge pricing on TNC operations and customer behavior, in order to develop policies and practices that promote equitable and sustainable TNC operations. It is also recommended that future research examines the potential impact of autonomous vehicles on mode shift, vehicle counts, travel time, speed, and vehicle kilometer traveled, in order to gain insights into how this emerging technology could impact operational performance in the presence of TNC services.

Moreover, data sharing between TNC companies and researchers is strongly encouraged to enable a better representation of actual TNC trips in transportation modeling, thus benefiting transportation agencies and TNC providers in meeting the travel needs of the public.

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