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Quantifying the Impact of Transportation Network Companies on Urban Congestion in a Medium Sized City

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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.

Key words: TNC, Uber, Lyft, on-demand ridesourcing, MATSim.

1. 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

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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.

2. 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.

2.1 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.

2.2 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 [16].

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.

3. Methodology

3.1 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.

3.2 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

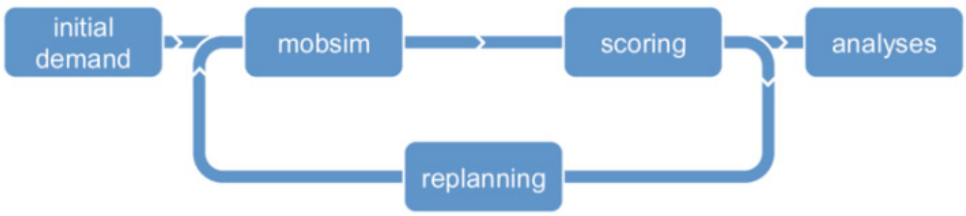

Fig. 1 The co-evolutionary algorithm of MATSim [17].

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.

3.3 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].

3.4 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.

4. Results

4.1 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.

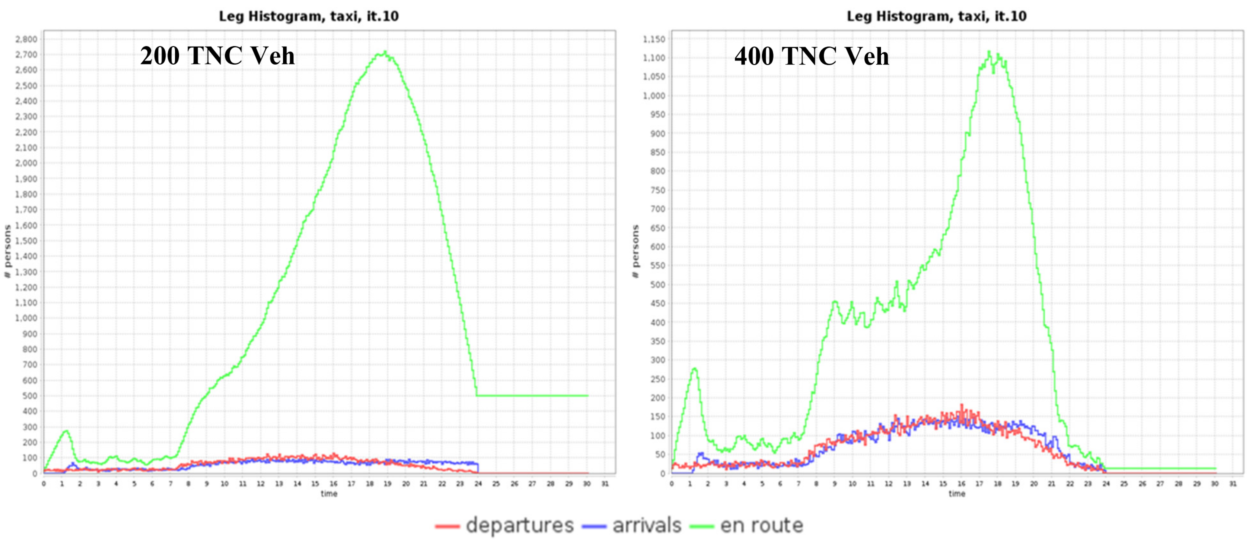

Fig. 2 Number and status of Uber rides by hour.

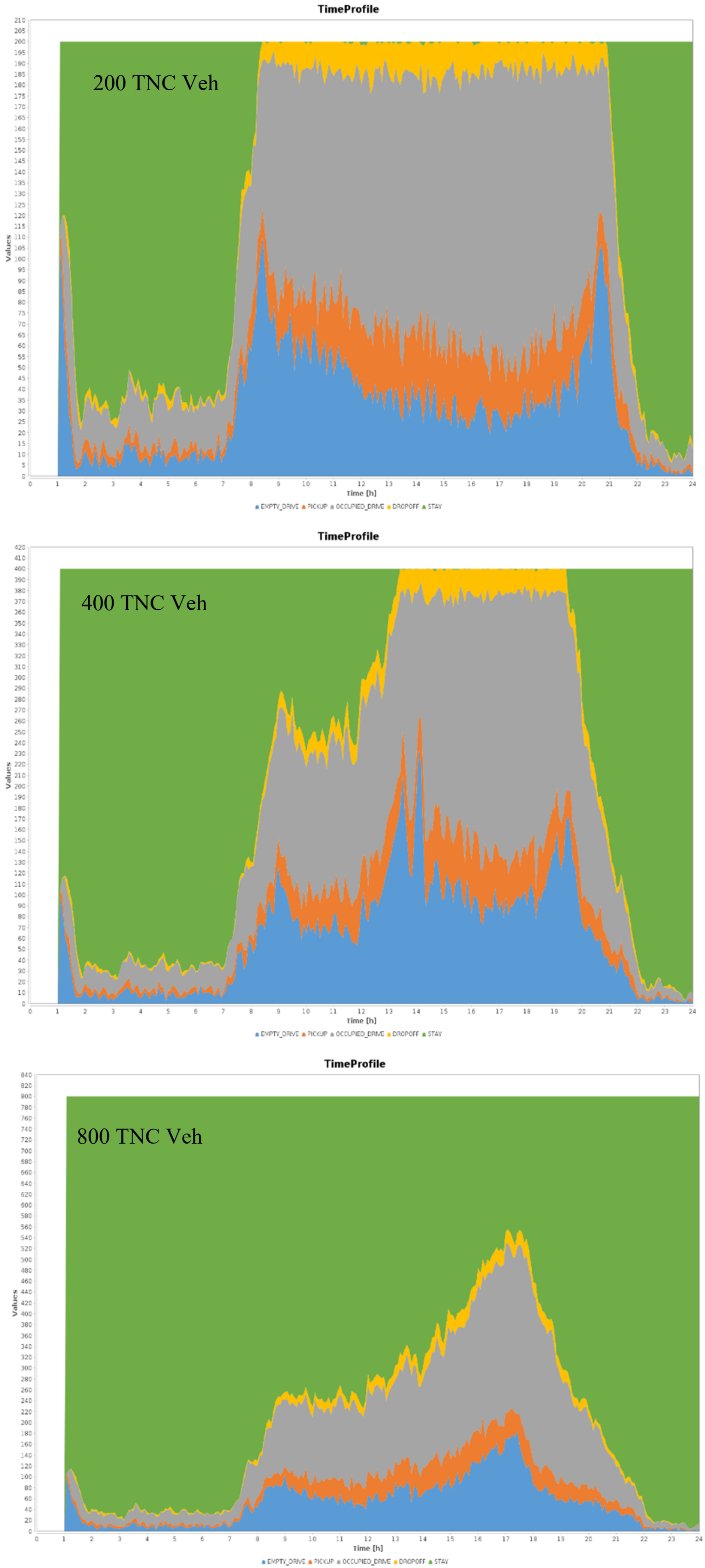

Fig. 3 TNC vehicle status statistics.

4.2 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.

4.3 Impact of TNC Service Availability on Network-Wide Operations

4.3.1 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.

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

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 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%

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	-	
	200 TNC Veh	2,764,169	-498,453	22.0%
TNC service available	400 TNC Veh	2,801,092	-535,376	23.6%
	800 TNC Veh	2,790,519	-524,803	23.2%

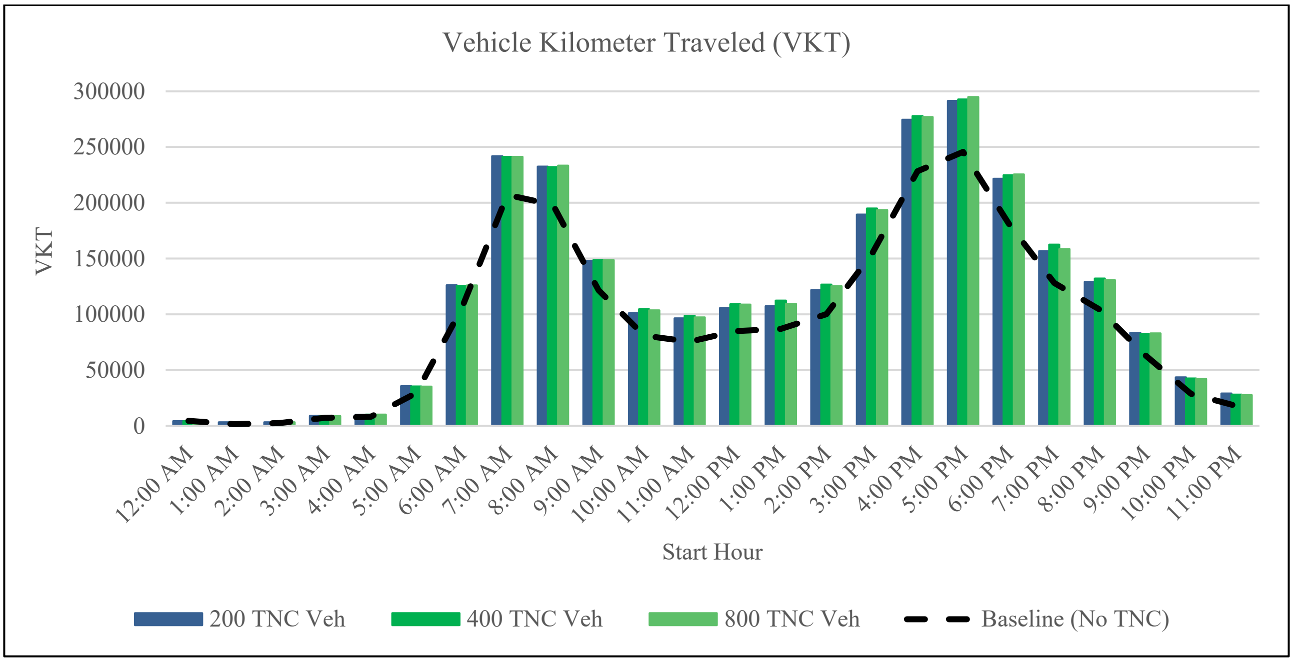

Fig. 4 Total VKT by hour of the day.

4.3.2 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.

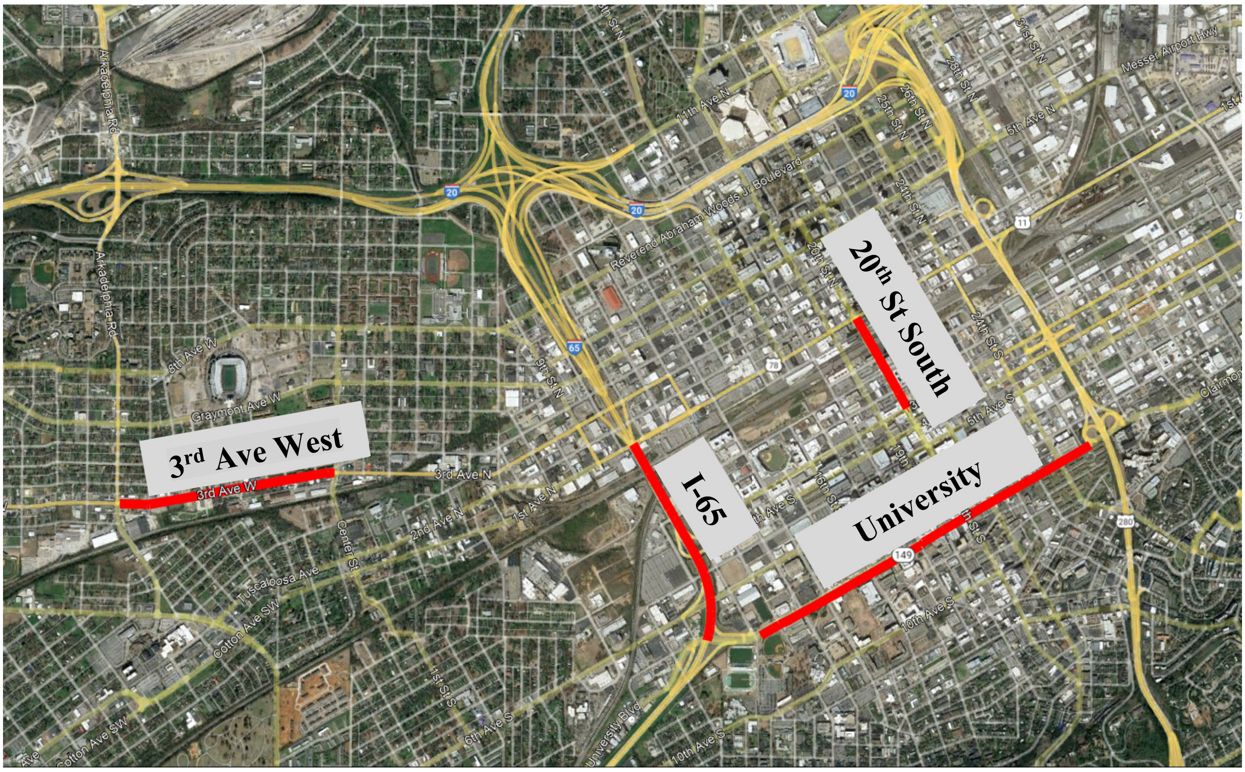

Fig. 5 Location of sample study corridors.

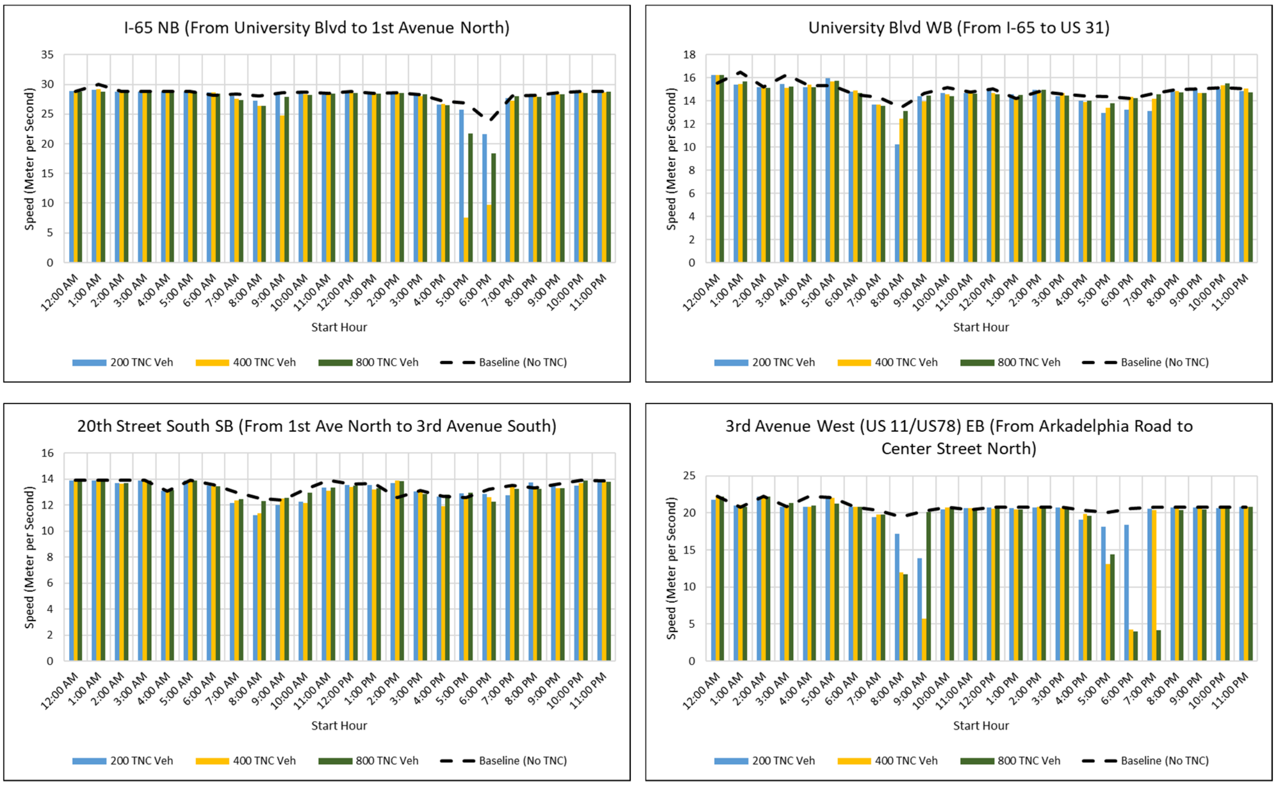

Fig. 6 Hourly average speed over 24 h for sample study corridors.

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

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

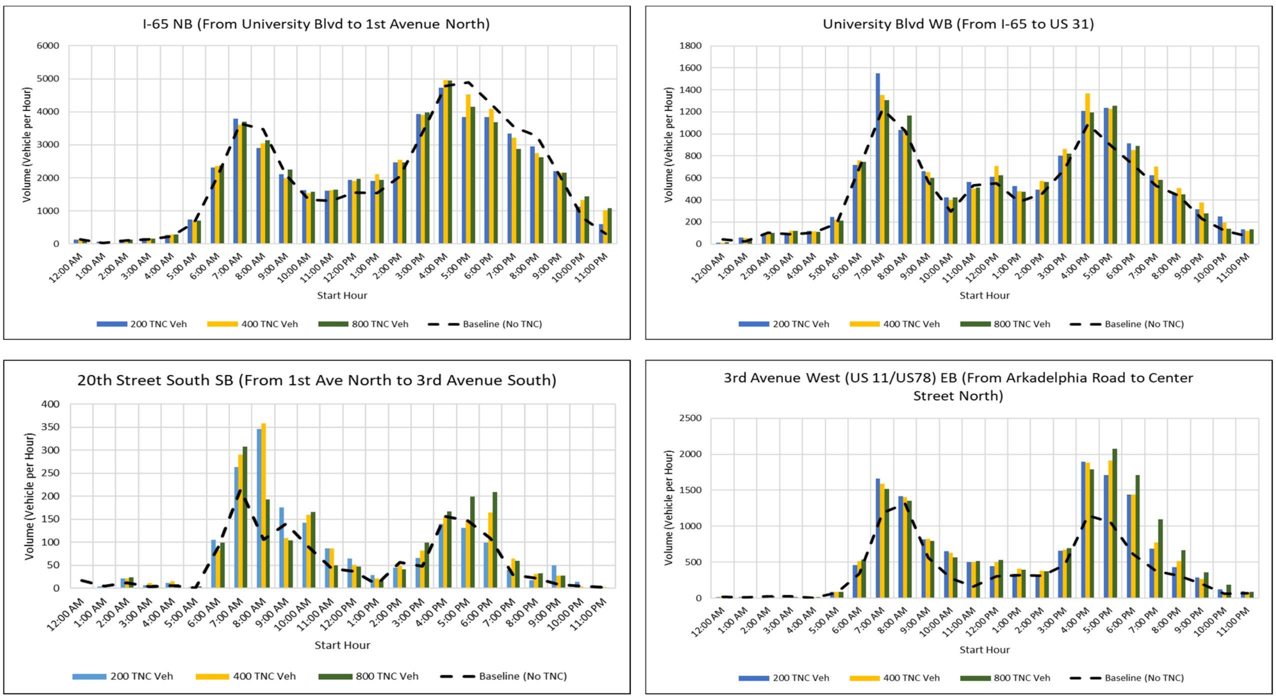

Fig. 8 Hourly average volume over 24 h for sample study corridors.

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.

5. 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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