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COVID-19 pandemic impacts on traffic system delay, fuel consumption and emissions

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ABSTRACT

A dramatic reduction in traffic demand has been observed during the COVID-19 pandemic, producing noticeable declines in traffic delays, energy consumption, and emissions. This unprecedented event provides us with the chance to investigate how limiting the number of vehicles on the transportation network can contribute to a better environment. This paper quantifies the effects of reduced traffic demand on vehicle delays, fuel consumption, and emission levels. Microscopic simulation was used to model traffic for seven different networks. Our results show that decreased traffic demand contributes significantly to reducing delays and emissions, especially in congested urban areas. The results also show that another important contributing factor is the network configuration. Specifically, networks with lower connectivity and fewer routing alternatives or networks with lower roadway density are more sensitive to traffic demand drops in terms of reducing vehicle delays and emissions.
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1. Introduction and literature review

The modern transportation system is composed of a large number of personal vehicles. For example, in the United States, there were 264 million registered vehicles in 2015. Given such numbers, traffic congestion, fuel consumption, and greenhouse gas emissions have become a serious problem. According to data from Forbes, traffic congestion cost US cities more than $88 billion in 2019 (FORBES 2020). Data from the US Energy Information Administration show that the transportation sector accounted for 28.2% of the total energy consumption in the US and contributed to 28% of emissions in 2018.[1]

Transportation engineers devote tremendous attention to reducing the negative traffic and environmental impacts generated by vehicles. Their efforts include increasing the capability of roads (adding lanes, widening roads, or building interchanges), implementing road pricing, improving the efficiency of internal combustion engines, identifying alternative power sources, optimizing the trajectories of vehicles by rerouting, eco-routing, or speed harmonization, and optimizing traffic control devices to decrease the frequency of acceleration and deceleration through traffic signal optimization, gating, and boundary control (Cairns, Atkins et al. 2001; Lo and Szeto 2005; Samaras and Meisterling 2008; Silva, Ross et al., 2009;

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[1] https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

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Earleywine, Gonder et al. 2010; Barth et al., 2011; AERIS 2012; Ahn et al., 2013; Ahn and Rakha 2014; McCoy and Stephens 2014; Bigazzi and Clifton 2015; Du, Guo et al. 2015; Elbery A. 2015; TRB 2016; Ma R. 2017; Litman 2018; Al-Masaeid 2019; Calle-Laguna, Du et al. 2019). However, the effects of such improvements are typically insignificant because the current transportation system is overloaded. The transportation system is running at its capacity and any method to improve its efficiency becomes marginal. The large number of vehicles is the solid base of the system, and any method of improvement can only scratch the surface of the problem.

Interestingly, the most effective possible solution to this problem has been the least investigated by previous research: decreasing the demand and the number of vehicles in the network. The reason is that, theoretically, this solution can never be achieved: people need to travel for work, leisure, running errands, and other purposes. According to the Bureau of Transportation Statistics (BTS), total vehicle miles traveled (VMT) on highways increased on average by 1% each year from 2000 to 2018, reaching 3240327 (millions, 2018) VMT, up from 2746925 (millions, 2000) (BTS 2019).

At the beginning of 2020, the COVID-19 pandemic became such a serious contagion that the whole world began to shut down. A Michigan-based transportation data management company, MS2, launched the Traffic Dashboard to provide timely information for monitoring the impacts. The daily traffic volume trends (DTVT), a metric about the daily traffic volume change compared to the same day of the week in the same month for the most recent year, was created and published to reflect the traffic volume changes across the US (MS2 2020). According to their data, overall national traffic has been cut down by up to 65%. Similar statistics have been provided by Google (Google 2020). In general, the reduction in traffic volumes ranged from 40% to 65% by state.

Due to this dramatic change in traffic volumes, reporters found that the air quality in the Los Angeles (LA) area improved phenomenally (CNN 2020). Cities with historically high levels of PM2.5 witnessed a dramatic drop in pollution since enforcing lockdowns (BBC 2020). This raises a question that seemed impossible to answer before, namely: to what extent can reduced traffic demand impact traffic congestion, vehicle fuel consumption, and emission levels? Are these impacts network specific?

The purpose of this paper is to study the changes in traffic delays, vehicle fuel consumption and emissions of the transportation system during this unprecedented pandemic. Multiple networks were selected to serve as the testbeds. The changes are explored for each network. Suggestions on policy making regarding pollution and delay control are provided accordingly.

2. Modeling methodologies

We estimate the changes in air pollution and congestion in a simulated environment with real-world calibrated traffic demands and networks. To accurately model the emissions and delays, three components are needed: a microscopic emission model (VT-Micro), a traffic simulation tool (INTEGRATION), and a software that can accurately estimate traffic demands (QUEENSOD). In this section of the paper, we will discuss these three modeling components.

The majority of existing emission models use average speeds to estimate large-scale, system-wide emissions at a macroscopic level. For example, the Motor Vehicle Emission Simulator (MOVES) is a US Environmental Protection Agency (EPA) emission modeling system that estimates emissions for mobile sources at the national, county, and project level for air pollutants, greenhouse gases, and air toxins (USEPA 2020). The advantage of such models is their straightforwardness. The output is at an aggregated level and can be used to describe the overall status of the system. However, the emissions and fuel consumption of vehicles are highly related to multiple factors, including the instantaneous speeds and accelerations of vehicles. With the same number of vehicles traveling in a network, different vehicle kinematics will generate completely different overall aggregated emission results. A more accurate method is to calculate the fuel consumption and emissions at a microscopic level and sum the results to show the aggregated effect. Therefore, in this study, we use the VT-Micro model to estimate the vehicle fuel consumption and emissions. VT-Micro is a polynomial fit that computes the instantaneous fuel consumption ($F(t)$) and emission rate ($E(t)$) as a function of the vehicle speed ($v(t)$) and acceleration ($a(t)$) levels, as demonstrated in Equation 1. $L_{i,j}$ and $M_{i,j}$ are model parameters that were calibrated using chassis dynamometer data collected at the Oak Ridge National Laboratory (ORNL) and data collected by the EPA with an R^2 of more than 0.92 (Ahn et al., 2002a, 2002b, 2002c). Fig. 1 (Rakha, Ahn et al. 2003; Rakha et al., 2004) illustrates a good fit between the instantaneous fuel consumption models (lines) and the ORNL data (symbols) for an average composite vehicle. The figure clearly demonstrates that vehicle accelerations have significant impacts on vehicle fuel consumption rates, especially at high speeds with the resulting high engine loads. A series of compatible vehicle emission models have been developed using the same ORNL data (Rakha et al., 2000 and Ahn et al., 2001). These models, which estimate hot-stabilized tail-pipe hydrocarbon (HC), carbon monoxide (CO), and nitrous oxide emissions (NOx) emissions, also operate on a second-by-second basis. As was the case with the fuel consumption models, the emission models are sensitive to the instantaneous vehicle speed and acceleration levels, as illustrated in the figure. The model also accounts for the ambient temperature, the extent to which a vehicle's catalytic converter has already been warmed up during an earlier portion of the trip, and high-emitting vehicles.

$$F(t)=\begin{cases}\exp\left(\sum_{i=0}^{3}\sum_{j=0}^{3}L_{i,j}\,v(t)^{i}a(t)^{j}\right) & \forall a(t)\geq 0\\ \exp\left(\sum_{i=0}^{3}\sum_{j=0}^{3}M_{i,j}\,v(t)^{i}a(t)^{j}\right) & \forall a(t)<0\end{cases} \tag{1}$$

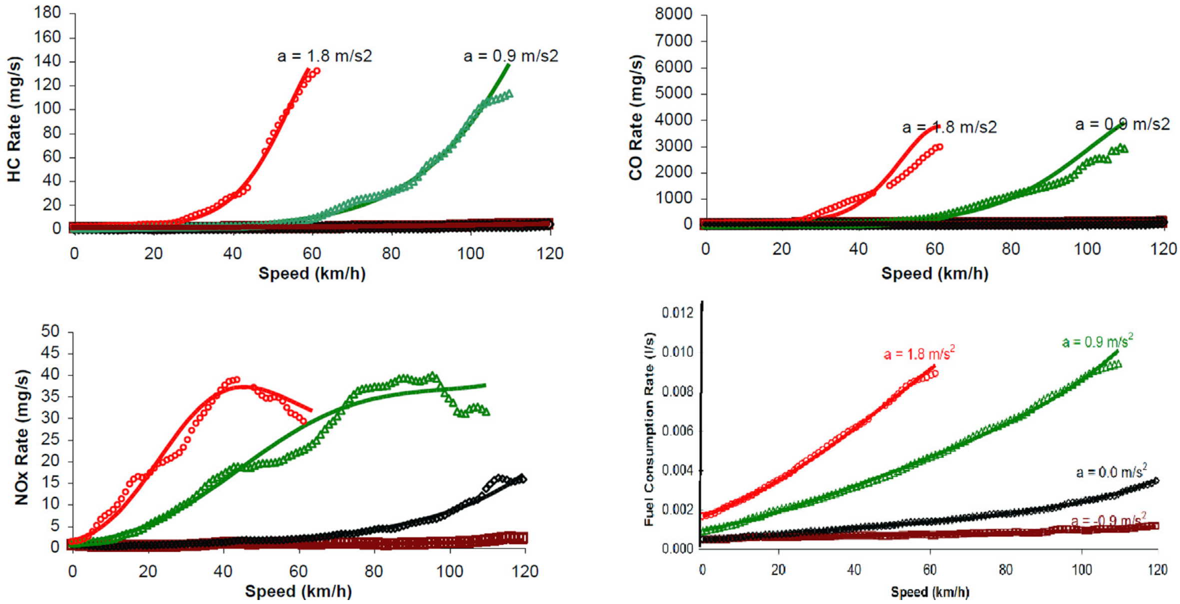

Fig. 1. Instantaneous fuel consumption and emissions based on ORNL data.

The VT-Micro model is incorporated in the INTEGRATION, an agent-based microscopic traffic assignment and simulation software (Rakha, Ahn et al. 2012). INTEGRATION was first developed by Van Aerde (Aerde and Rakha 2007; Van Aerde and Rakha 2013) and has been enhanced through the years. It permits the analysis of many dynamic traffic phenomena, such as shock waves, gap acceptance, and weaving. It can consider virtually continuous time-varying traffic demands, routings, link capacities, and traffic controls without the need to predefine an explicit time-slice duration between these processes. It allows considerable flexibility in terms of representing spatial variations in traffic conditions. Embedded with carefully calibrated modules, including link speed-flow relationships, multi-path equilibrium traffic assignment, and uniform, and random and/or over-saturation delay, INTEGRATION can model traffic and their associated fuel consumption and emissions at both the macro and micro level using the embedded VT-Micro module.

The traffic demand was calibrated using the QUEENSOD software (Van Aerde et al., 2003), which computes the most likely static traffic assignment and origin–destination (OD) demand by iteratively minimizing the error between the observed traffic counts obtained from selected loop detectors and the corresponding estimated traffic volume. The traffic count data needed to generate the synthetic OD files are first obtained from stationary detectors (e.g. loop detectors) or probe vehicles and some estimate of a seed OD matrix that can be obtained using the traditional trip generation model. The synthetic OD demand was calibrated with PEMS loop detector data or local transportation planning data. Dynamic OD demands were then estimated using an iterative procedure described in the literature (Yang and Rakha 2019). The final estimated OD matrix typically provides a good match to the field-observed traffic counts with an R^2 above 0.9. Fig. 2 shows the accuracy of the simulated link flows for one of the networks selected in this study (subnetwork 3, downtown LA).

3. Simulation and results analysis

Seven simulation networks were used as testbeds for this paper. All were heavily congested metropolitan areas. Testbed 1 through 5 are subnetworks in LA. Testbed 6 is in Doha, Qatar, and Testbed 7 is a section of I-66 in the Washington, D.C. area.

The greater LA area is a huge network with more than 3 million residents. The network and traffic demand were created and calibrated with local planning data in a previous research effort (Du et al., 2018; Elbery et al., 2018). Due to the large size of the network, we divided the network into five subnetworks with calibrated overall and subnetwork traffic demands (Fig. 3). Subnetwork 1 is the northwest part of LA. This subnetwork is composed of several major arterials cutting through the Hollywood area. A large portion of this subnetwork is composed of arterial roads. Subnetwork 2 is located at the west part of the downtown area. I-10 and I-405 serve as the two connecting freeways linking north–south and east–west of the subnetwork. Subnetwork 3 covers the east part of LA, a grid of downtown local roads encircled by freeways connecting the downtown with external areas. It includes the Central Business District (CBD) area surrounded by freeway I-10 and I-110. This is. There is a high percentage of local roads in this network. Subnetwork 4 is located at the southeast corner and is less crowded than the previous three subnetworks. Subnetwork 5 is the least congested area of the five, with I-405 running through it as the major arterial. It is a mixed residential and commercial area. The simulation period for all five subnetworks was from 6 a.m. to 10 a.m.

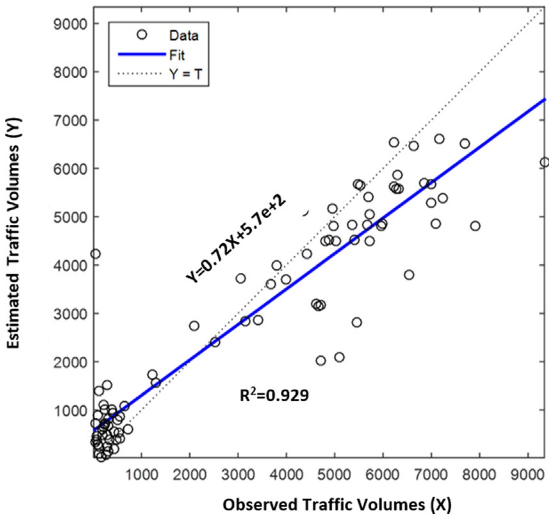

Fig. 2. Accuracy of calibration for OD demand in downtown LA.

Fig. 3. Simulation testbed (five LA subnetworks).

The sixth testbed is Doha, Qatar (Fig. 4). The Doha area is a highly congested network with large-scale traffic roundabouts and arterials. This network has many two-lane roundabouts and multiple-lane arterial roads but very few limited-access freeways. The simulation period was from 7 a.m. to 8 a.m. The seventh testbed is the I-66 area, located in Arlington, Virginia (Fig. 5). Four major arterials and a freeway are incorporated in the network coding: I-66, I-495, US-29, and US-50. Local

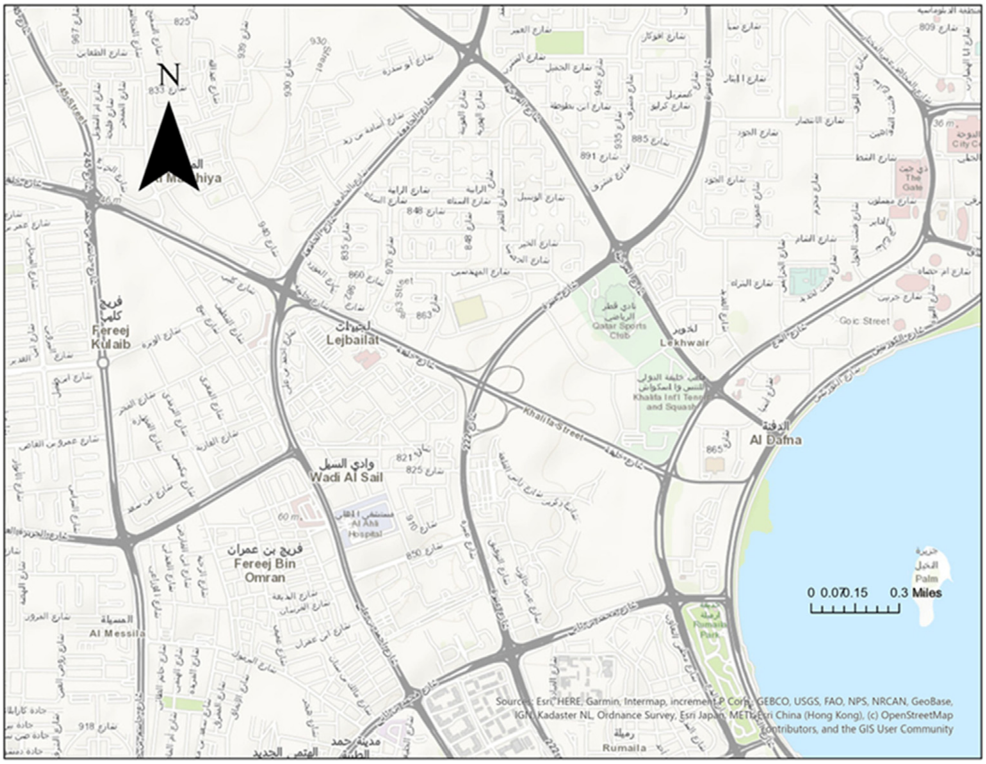

Fig. 4. Simulation testbeds – Doha.

Fig. 5. Simulation testbeds I-66 in Washington, DC.

Table 1
Travel statistics of the seven testbeds.

Network	Average Trip Length (km)	Original Delay (min/VMT)	Number of Links	Number of Nodes	Total Calibrated Traffic Demand (Veh Trips in 4 hours)
LA SUB1	8.7	2.1	1,795	779	423,000
LA SUB2	6.6	2.4	2,261	941	459,000
LA SUB3	6.5	1.5	3500	1600	562,000
LA SUB4	6.9	2	1830	764	450,000
LA SUB5	7.3	1.6	1507	647	365,000
Doha	3.2	10.8	301	169	30,000
I-66	15.0	1.3	870	601	139,000

access roads for residential areas are included as well. The resulting simulation network covers an area 16 miles long and 2 miles wide. This network is a heavily traveled corridor connecting northern Virginia and Washington, D.C. I-66 aligns east–west, with parallel local arterial alternative routes, to serve commuting traffic. The simulation period was from 6 a.m. to 9 a.m. Table 1 lists the statistics of the trips in the seven testbeds.

Since the outbreak of coronavirus, traffic volumes decreased dramatically across the US. Multiple states announced stay-at-home orders that recommended canceling trips except for essential activities. On average the traffic volume decreased by 45% to 55% (MS2 2020). The number varies depending on how badly coronavirus hit an area. A similar amount of reduction in the usage of Apple Map is reported as well[2]. As shown in Fig. 6, Virginia observed a drop of 50% at the lowest point in April and LA saw more than a 60% drop in traffic volumes during the same time. Similar to the United States, Qatar observed a reduction in traffic demand ranging between 5% and more than 50% (Fig. 7). Google prepared a mobility report to help people understand responses to the pandemic (Google 2020). The report charted movement trends (number of visitors or time spent in) across different categories of places, such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. Although not directly, the Google mobility report can be used to describe the changes in the overall traffic volumes. As shown in Table 2, the mobility volume to the transit stations decreased the most, and visits to grocery and pharmacy, which are counted as essential trips, decreased by 20% as well (see Figs. 9–11).

In the simulation runs, we tested the effects of reduced demand by applying a reduction factor ranging from 5% to 55% to the original demand level, to replicate real traffic reduction trends starting from the beginning of the pandemic. A single simulation run was performed with a 5% coefficient of variation in link travel speeds. This produces stochasticity in driver car-following behavior. The sensitivity of delay, emission levels, and fuel consumption changes by the demand change was calculated. The results are illustrated in Figs. 8–12 (five LA subnetworks) and Figs. 13 and Figs. 14 (Doha and I-66).

The double orange lines represent the change in traffic demand levels. The results for the five LA networks are similar. The benefits for delay with decreased demand are more significant at the beginning of the demand decrease: a 5% decrease in traffic demand generates up to a 25% drop in the average vehicle delay. To achieve a 50% reduction in delay, the demand level needs to decrease by approximately 15% to 20%. The delay decreases continuously when the demand drops without any obvious plateau. Meanwhile, the emissions and fuel consumption levels follow a similar trend but are slightly greater in magnitude than the decreased demand. The emissions and fuel consumption levels decrease by approximately 65–70% when the demand level decreases by 55%.

In the Doha area, the first 5% demand reduction generated a nearly 40% reduction in delay, 30% reduction in fuel consumption, and 30% reduction in CO_2 emissions. Compared to the LA networks, the Doha network has a more varied benefit for each type of emission. The most significant benefit generated by reduced demand is for CO_2 and fuel, and the least is CO emissions. To achieve a 50% reduction in CO_2 and fuel consumption, the demand only needs to drop by 15%. The curve for delay starts to level out when the demand decreases by 30%. When the demand drops to 45% of the original level, delay decreases to only 0.9 minutes per vehicle per kilometer (VKM) traveled, accounting for only 9% of the original delay. At this demand level, CO_2 and fuel consumption drop more than 80%. NO_x and HC are reduced more than 70%, and CO reaches a 60% reduction.

For the I-66 corridor, to reach a 50% reduction in delay, the demand level only needs to drop by 15%. The rate of decrease in delay starts to level out when the demand decreases to 60% of the original level. When the demand level decreases from 100% to 45%, the delay improves significantly. The average delay per VKM traveled is only at about 0.12 minutes, only 9% of the original delay, when the demand drops to 45%. Compared to delays, emissions and fuel consumption levels decrease at a less aggressive but still much sharper rate compared to the drop in demand. The emissions and fuel consumption levels decrease by almost 70% when the demand level decreases by 55%.

These simulation results demonstrate that delays can be significantly decreased with a slight decrease in vehicular demand. For example, a 10% demand reduction can generate up to a 50% reduction in vehicle delay. The effect on traffic delay is the most significant result from demand changes. Although not as dramatic as the changes in delay, emissions and fuel consumption all decrease noticeably, at a significantly larger pace compared to the demand change. This improvement is

[2] https://covid19.apple.com/mobility.

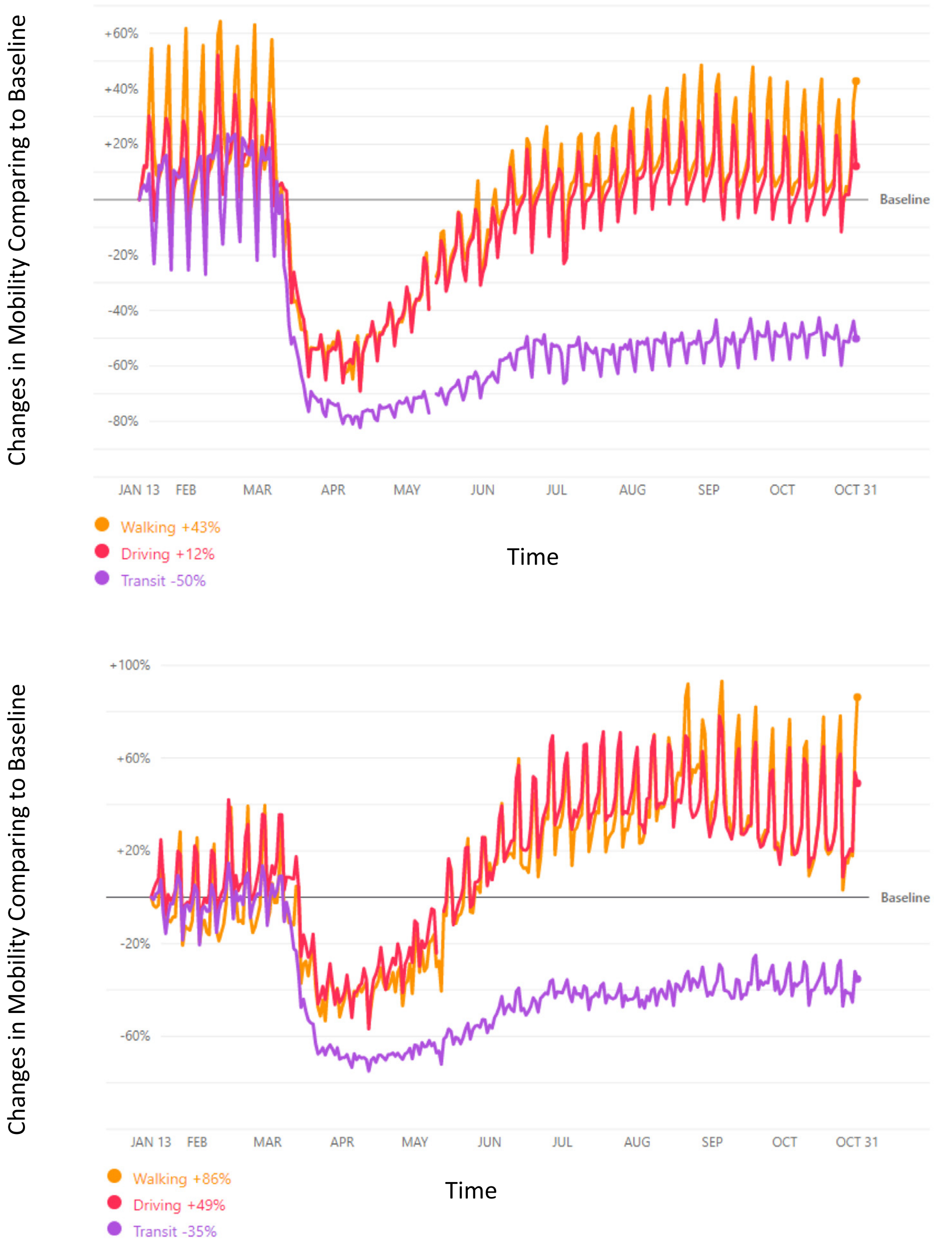

Fig. 6. Reduction in Apple Map Usage in Los Angeles (Above) and Virginia (Below).

especially noticeable at the beginning of the demand reduction, especially for LA and Doha. The associated emissions and fuel consumption are typically more than double the reduction rate of the demand.

4. Network features and the effect of configuration

The different results of the testbeds from reduced demand generate an interesting question: What factors impact the effects of reduced demand on the transportation system? We then examined the network features and the topological and structural features of the seven testbeds (Table 3).

As can be seen, the five LA subnetworks have similar network features. All five LA subnetworks are larger in scale with a high percentage of arterials and traffic-signal-controlled intersections. The Doha network covers a much smaller area with a

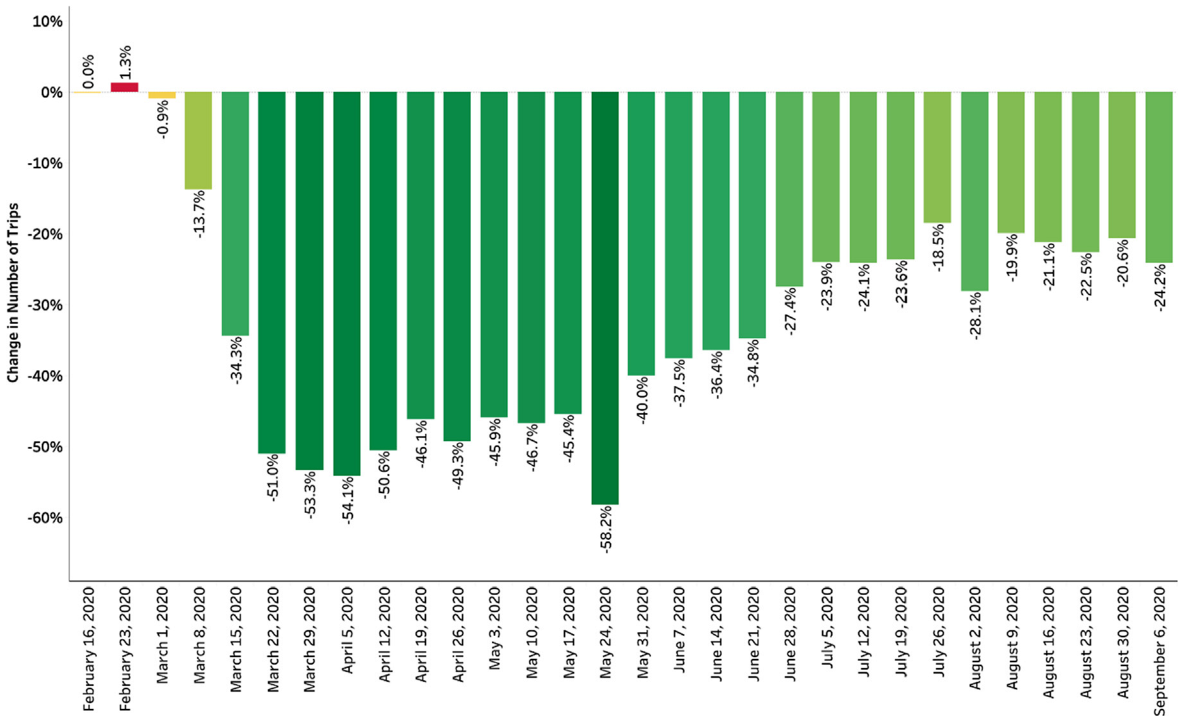

Fig. 7. Demand reduction in Doha, Qatar (Source: Qatar Mobility Innovations Center (https://twitter.com/QmicQatar/status/1298975977188601856.)).

Table 2
Mobility volume changes by destination (data retrieved up to April 10, 2020).

	Retail and Recreation	Grocery and Pharmacy	Parks	Transit Stations	Work
Virginia	−44%	−18%	22%	−56%	−39%
California	−53%	−27%	−61%	−59%	−42%
Nationwide	−49%	−20%	−20%	−54%	−40%

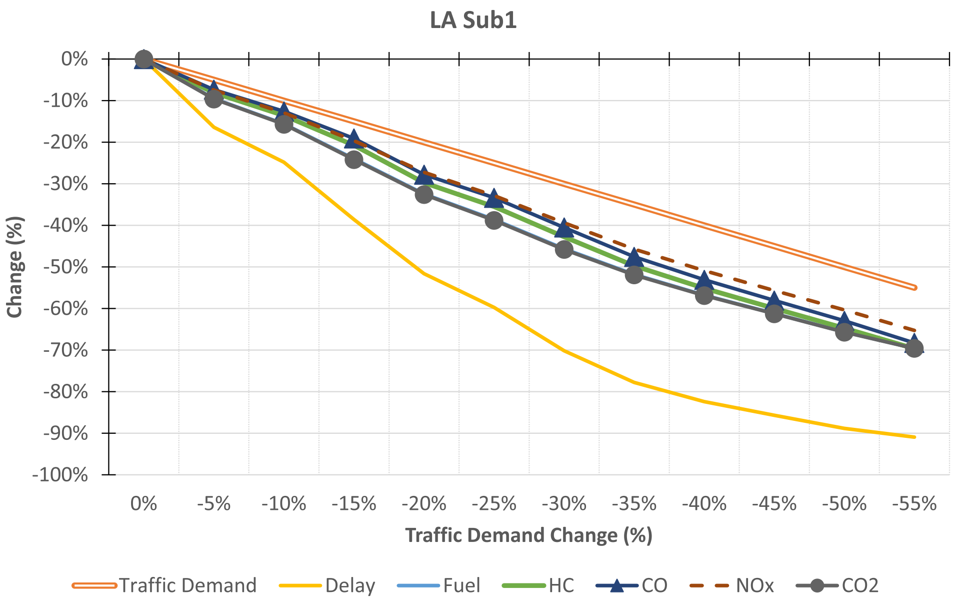

Fig. 8. Changes in LA subnetwork 1.

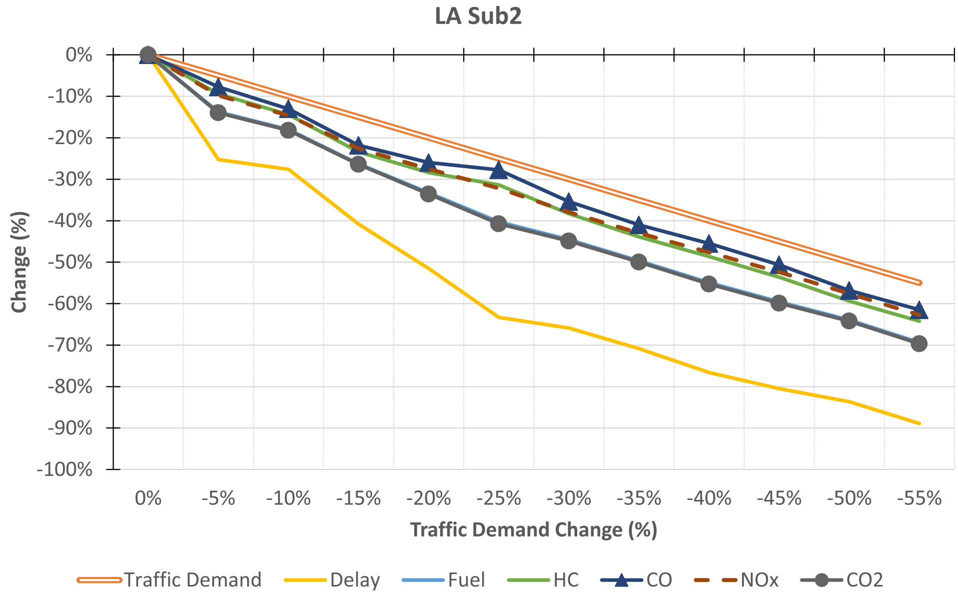

Fig. 9. Changes in LA subnetwork 2.

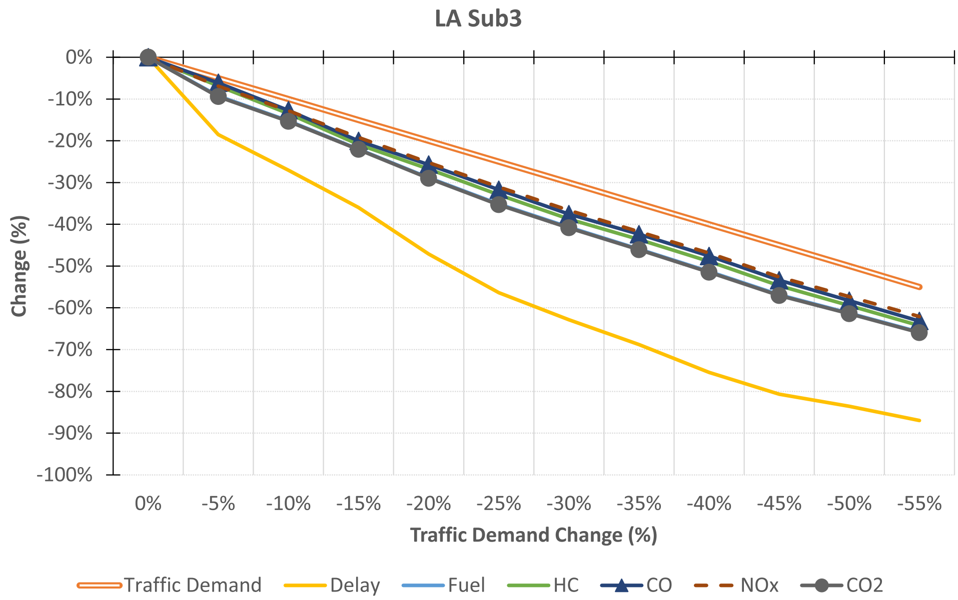

Fig. 10. Changes in LA subnetwork 3.

larger percentage of local roads. All the intersections in Doha are traffic signal controlled. The I-66 area has the largest percentage of freeways and a high percentage of yield-controlled intersections.

To further investigate the connectivity and development of each network, we used graph theory measures to quantify the topological and structural features of the networks (Eqs. (1)–(6)). All the indices we select here are well-defined and are used regularly to describe the topological and structural features of networks. According to the definitions of these indices, each describes one aspect of the connectivity of the network (Rodrigue 2020; Sahitya and Prasad 2020; ShippensburgUniversity 2020). The α parameter is a measure of connectivity that quantifies the number of cycles in a graph in comparison to the maximum number of cycles. The β parameter measures the average number of edges per vertex (average number of links per node). The γ parameter measures the connectivity that considers the relationship between the number of observed links and the number of possible links. The Cyclomatic Number (CN) is essentially the number of closed circuits in the graph. It is a measure of route redundancy. The sum index ATS is used to describe the overall connectivity of a network. Road density

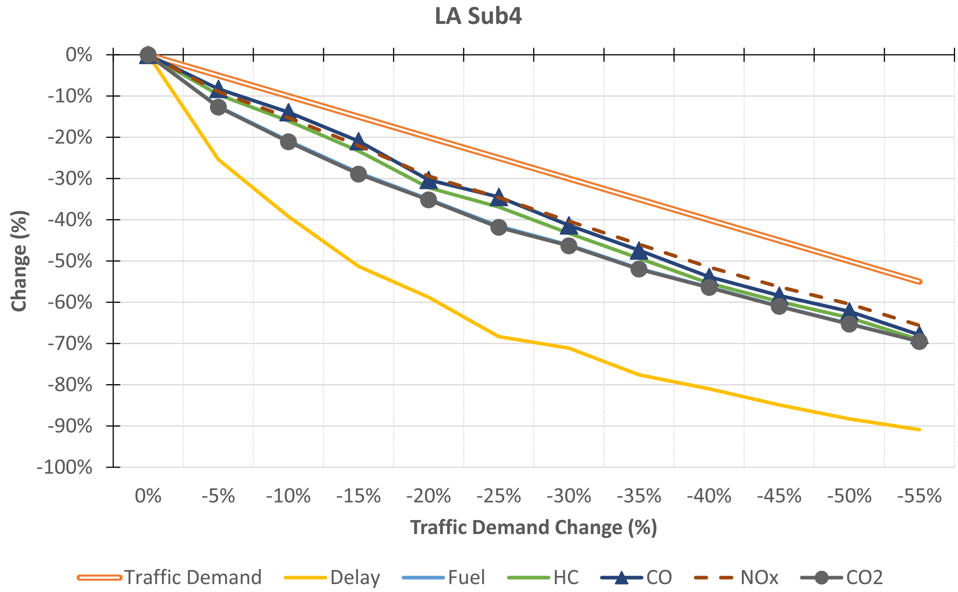

Fig. 11. Changes in LA subnetwork 4.

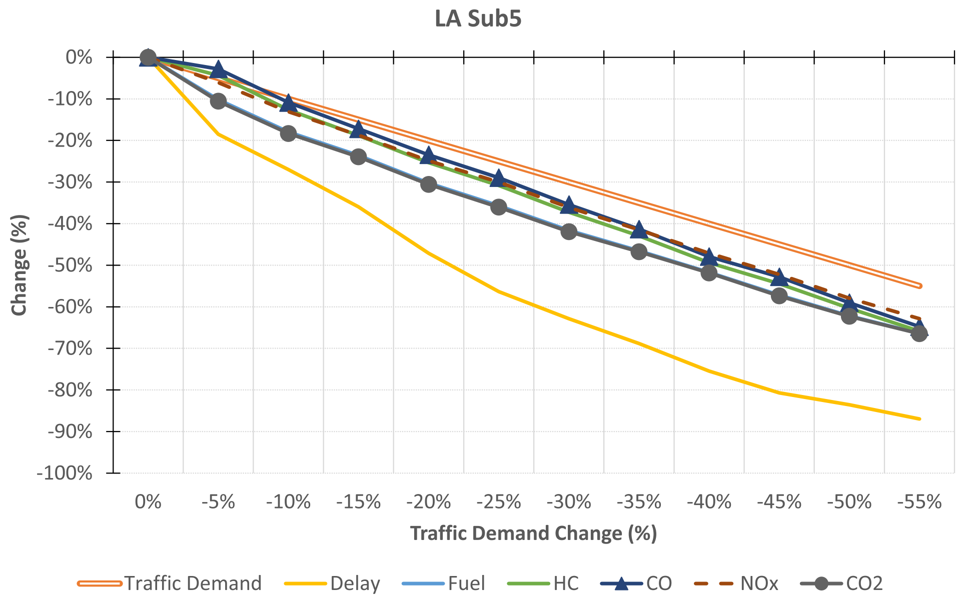

Fig. 12. Changes in LA subnetwork 5.

defines the total length of road links in a network in a unit of area. This index helps us to understand the degree of development of a road network (Table 4).

$$\text{Alpha Index}: \alpha = (l - n + 1)/(2n - 5) \tag{1}$$

$$\text{Beta Index}: \beta = l/n \tag{2}$$

$$GammaIndex: \gamma = l/(3 * (n - 2) \tag{3}$$

$$\text{Cyclomatic Number}: CN = l - n + 1 \tag{4}$$

$$ATS = \alpha + \beta + \gamma + CN \tag{5}$$

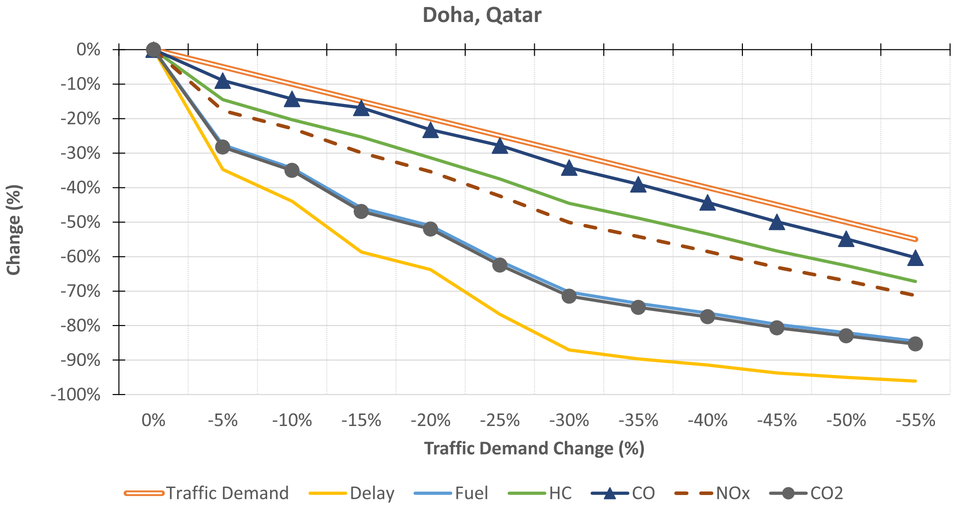

Fig. 13. Changes in Doha.

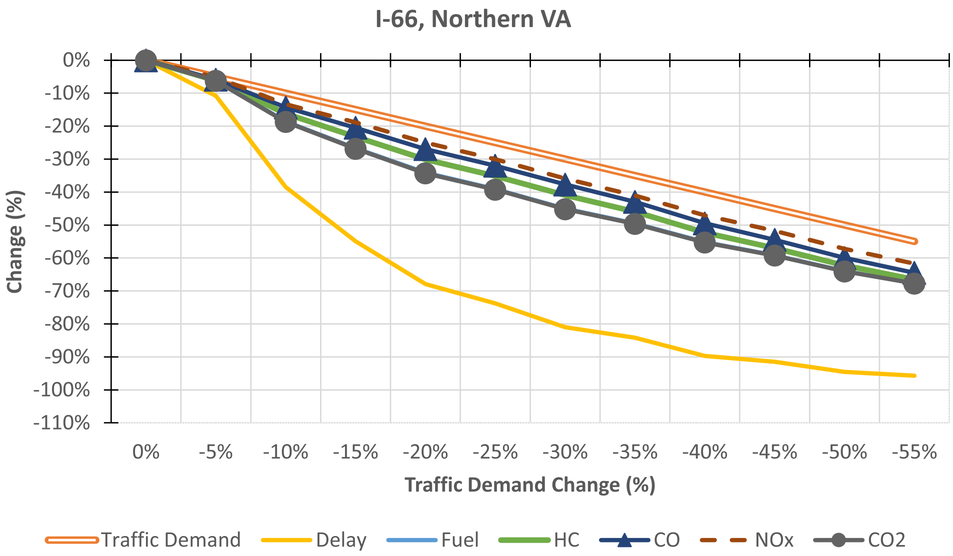

Fig. 14. Changes in I-66.

$$\text{Road Density}: RD = \frac{Road\ \ Network\ \ Length(KM)}{Covered\ \ Area\ \ (sSqaureKM)} \tag{6}$$

where $l=$ number of links and $n=$ number of nodes

As can be seen, the Doha network is significantly different from the networks in the US in topology and structure. The comprehensive connectivity index ATS is much smaller than the rest of the networks. The road density is significantly smaller as well. From the effects of delay relief and emission reduction caused by the COVID-19 pandemic, Doha has the most significant results with reduced delays and emissions. From Table 4, we can infer that a lower connectivity is likely one of the factors that contributes to the better the results achieved by reducing the traffic demand.

5. Conclusions and discussions

The results from this paper show that reducing the traffic demand is a very effective method to reducing traffic congestion and air pollution. A 15% reduction in traffic demand for congested networks can generate as much as a 60% reduction in delay. Although not as dramatic as the delays, emissions and fuel consumption levels all decrease at a much larger rate

Table 3
Features of the seven testbeds.

	Area (km^2)	Freeways[1] (Links/Link Miles)	Arterials[3] (Links/Link Miles)	Locals[3] (Links/Link Miles)	Intersections		
					Signalized	Stops	Yields
LA SUB1	207	17.1% (286/163)	81.8% (1472/781)	1.1% (37/10)	86.8%	10.5%	2.7%
LA SUB2	228	9.7% (132/94)	87.4% (2057/844)	2.9% (71/28)	88.9%	10.7%	0.4%
LA SUB3	168	16.7% (382/188)	81.8% (3119/924)	1.6% (72/18)	83.8%	14.9%	1.3%
LA SUB4	184	15.3% (177/142)	84.1% (1631/778)	0.5% (22/5)	82.9%	13.1%	4.0%
LA SUB5	189	19.3% (199/151)	79.9% (1294/623)	0.8% (14/6)	83.7%	15.2%	1.0%
Doha	5	11.5% (17/7)	63.3% (195/40)	25.2% (89/16)	100.0%	0.0%	0.0%
I 66	70	26.5% (99/105)	56.3% (558/222)	17.2% (213/68)	89.0%	1.7%	9.2%

[1]Percentages by road types listed in the table are percentages in link mileages.

Table 4
Topological and structural features.

	Alpha	Beta	Gamma	Cyclomatic Number (CN)	ATS	Road Density (KM/Square KM)
LA SUB1	0.23	1.45	292787.33	351	293140.01	4.61
LA SUB2	0.18	1.35	398873.33	333	399207.86	4.24
LA SUB3	0.20	1.40	1237062.33	654	1237717.94	6.73
LA SUB4	0.20	1.39	269847.67	298	270147.25	5.02
LA SUB5	0.18	1.36	189062.67	232	189296.20	4.12
DOHA	0.24	1.46	13832.00	79	13912.70	0.33
I66	0.18	1.35	162200.00	211	162412.53	2.09

compared to the demand change. For example, a 55% reduction in traffic demand typically can generate up to a 90% reduction in greenhouse gas emissions and fuel consumption levels.

Factors that may influence the effects of reduced demands on emissions and congestion include the initial congestion level, the percentage of arterials and signal-controlled intersections, the topological network configuration, and roadway density in the area. Initially, more congested areas have a sharper drop in delay at the beginning of the decrease in demand. A network with more lower-speed local roads and more signal-controlled intersections is more sensitive to the initial demand reduction. Meanwhile, a network with less connectivity and lower roadway density benefits more from the demand reduction.

The findings of this study suggest that curbing the number of vehicles on roads is a very effective tool. As such, policy makers should consider suppressing overall demand levels after the pandemic subsides by increasing teleworking, carpooling, and the use of public transit, as well as using new technologies such as mobility credits (Fujii, Gärling, & Kitamura, 2001; Moser, Blumer, & Hille, 2018; H. Yang & Wang, 2011). Such changes in travel behavior will have substantial benefits on the transportation system. We believe that maintaining a relatively lower demand, even if the reduction of traffic volume is not significant, will generate huge benefits for the environment.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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