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TRANSPORT FINDINGS

Preliminary Investigation of COVID-19 Impact on Transportation System Delay, Energy Consumption and Emission Levels

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Transport Findings

A dramatic reduction in traffic demand was observed during the pandemic of COVID-19 producing noticeable reductions in traffic delay, energy consumption, and emissions. This unprecedented event provides us with a perfect 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 air pollution and greenhouse gas emissions. Microscopic simulation is used to model traffic and their associated emissions. Our results show that the decreased traffic demand contributed significantly to decreasing vehicle delays and emissions, especially in congested urban areas.

RESEARCH QUESTION

The modern transportation system is composed of a large body of personal vehicles, which contributes significantly to air pollution. Specifically, studies showed that the transportation sector consumed 28% of the total energy consumption in the US and contributed to 27% of the total emissions in 2013 (USEPA 2013a, 2013b). To mitigate these negative environmental impacts, tremendous research effort has been conducted to try to curb the use of personal vehicles and increase the capacity of the road network. However, since the current road network has already reached its capacity, the effects of such improvements are marginal. The most effective possible solution to this problem is decreasing the traffic demand.

COVID-19 generated a bold opportunity for us to witness the effects of reducing traffic demand. The overall US national traffic decreased by up to 65% by the end of April (Google 2020; MS2 2020). Meanwhile, reporters found that the pollution in the Los Angeles area phenomenally improved (CNN 2020). Cities with historically high levels of PM2.5 have witnessed a dramatic drop in pollution since enforcing lockdowns (BBC 2020).

The purpose of this paper is to attempt to quantify the impact of the reduced traffic demand associated with the COVID-19 travel restrictions on vehicle delay, fuel consumption, and emission levels. We will attempt to answer two research questions, namely: (1) to what extent can reduced traffic demand impact vehicle delay, fuel consumption, and emission levels? And (2) are these findings network specific?

METHODS AND DATA

Vehicle fuel consumption and emission levels were quantified in a microscopic traffic simulation environment. Two software components were used: INTEGRATION and QueensOD. The INTEGRATION software uses the VT-Micro model to compute second-by-second vehicle fuel consumption and emission levels. VT-Micro is a polynomial regression model that computes the instantaneous fuel consumption ($F(t)$) and emission rate ($E(t)$) as a function of the instantaneous vehicle speed ($v(t)$) and acceleration ($a(t)$) levels, as demonstrated in Equation 1. Where $L_{i,j}$ and $M_{i,j}$ are the model parameters that were calibrated using chassis dynamometer data collected at the Oak Ridge National Laboratory and data collected by the US Environmental Protection Agency (EPA). The model produced good fits to the empirical data (an R^2 of more than 0.92) (Ahn et al. 2002; Rakha, Ahn, and Trani 2003, 2004).

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

The VT-Micro model is incorporated in the INTEGRATION software, an agent-based microscopic traffic assignment and simulation software (Rakha, Ahn, and Moran 2012; Van Aerde and Rakha 2013a, 2013b). INTEGRATION tracks vehicle lateral and longitudinal movements at a frequency of 10 Hz. The vehicle trajectories and lateral movements have been validated against empirical data (Rakha and Zhang 2003; Wang, Rakha, and Fadhloun 2017). The model computes the associated vehicle fuel consumption and emission levels every second, which are then summed up for the entire trip and for all the vehicles traversing the network to provide macro level output.

The traffic demand was calibrated using the QueensOD software (Van Aerde, Rakha, and Paramahamsan 2003), which computes the most-likely static traffic assignment and OD demand by iteratively minimizing the error between observed traffic counts obtained from selected loop detectors and the corresponding estimated traffic volume. The model also used a seed matrix obtained from the standard four-step planning process. Dynamic OD demands were then estimated using an iterative procedure described in (Hao Yang and Rakha 2019). The estimated OD matrix provided a good match to the field observed traffic counts with an R^2 of 0.9. Figure 1, compares the estimated and observed flows for the downtown LA network, one of the testbeds. A detailed description of the demand calibration effort is provided in (Du et al. 2018).

Figure Accuracy of Calibration for OD Demand in LA downtown

Two locations were selected as the testbeds for this study. As shown in Figure 2, the simulation network for the I-66 corridor includes 1,777 links and 50 signalized intersections, covering an area of 32 square miles (16 miles long and 2 miles wide) considering the morning peak traffic demand from 6 to 9

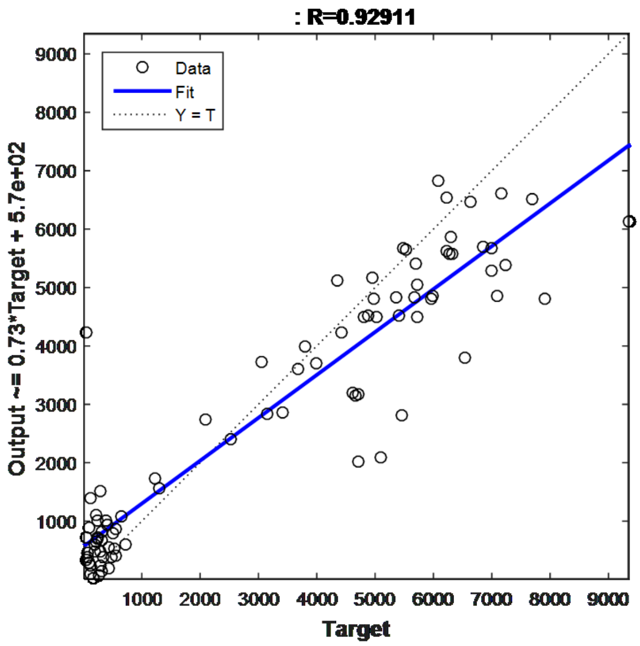

Figure 1: Accuracy of Calibration for OD Demand in LA downtown

Table 1: Features of the Two Testbeds

	Freeways (Limited Access)	Arterials (30-50mph)	Local Roads (Below 30mph)	Traffic Controlled Intersections		
				Signalized	Stop	Yield
I 66	11%	64%	24%	70%	5%	25%
LA	10%	0.5%	89%	60%	37%	3%

am. The downtown Los Angeles network is composed of 3,500 links, 1,600 nodes, and 457 signalized intersections. The traffic demand was calibrated for the morning peak period from 7 to 10 am. The two testbeds were selected to represent two typical network configurations. The first is a heavily traveled corridor connecting northern Virginia and Washington D.C. by a major freeway, I-66, with parallel local arterial alternative routes. The second is a typical downtown grid network surrounded with a number of freeways connecting the downtown to the various suburbs. The estimated OD demand matrices included 140,000 trips for the I-66 network, 530,000 trips for downtown LA network, respectively. The main features and configuration of the two networks are listed in Table 1. The LA downtown network has a much higher percentage of local roads and stop controlled intersections compared to the I-66 corridor.

Since the outbreak of the coronavirus, dramatically decreased traffic volumes have been observed worldwide. In this study, we tested the effects of reduced traffic volumes by applying a reducing factor ranging from 5% to 55% of the

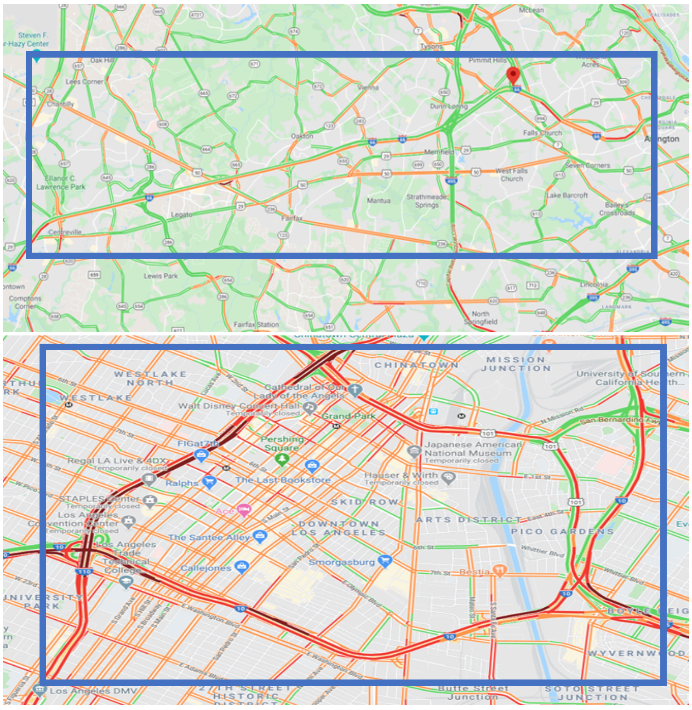

Figure 2: Simulation Testbed (I 66 in Arlington, VA, above, and Los Angeles downtown, below)

From maps.google.com.

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original demand level, resembling that of real traffic reduction trends starting from the beginning of the pandemic to later. The changes in the network-wide fuel consumption and emission levels for each of the demand levels was quantified and compared to the base demand level.

FINDINGS

The results are illustrated in Figure 3. The double orange lines represent the traffic demand level changes. For the I-66 corridor, the original delay is 5.1 seconds per Vehicle Kilometer (VKM) traveled (average trip length 15km). 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 the 60% of the original demand level. When the demand level decreases from 100% to 45%, the delay reduces significantly. The average delay per VKM traveled is only at about 0.5 seconds, which is 10% of the original delay, when the demand drops to 45% of the original demand. Comparing to delays, emissions and fuel consumption levels decrease at a less aggressive, but still at a sharper rate compared to the demand drop. The emissions and fuel consumption levels decrease by 65% when the demand level decrease by 55%. Los Angeles has a starting delay of 13 seconds per VKM traveled (average trip length is 6.5km), which is more congested than the I-66 corridor. The benefits with decreased demand are more significant compared to the I-66 corridor at the beginning of the demand decrease; a 5% decrease in traffic demand generates a 20% drop in average delay. To achieve a 50% reduction in delay, the demand level needs to decrease by 20%. The delay decreases continuously when

Figure 3: Changes in Delays, Emissions and Fuel Consumption Levels (I-66 above, LA downtown below)

the demand drops without any obvious plateau. Meanwhile, the emissions and fuel consumption levels follow a similar trend for both networks. The emissions and fuel consumption levels decrease by approximately 65% when the demand level decreases by 55%.

These results show that reducing the traffic demand is very effective in reducing traffic congestion and air pollution. Specifically, a 15% demand reduction can generate as much as a 50% delay reduction, depending on the initial congestion level. Initially more congested areas have a sharper drop in delay when the demand decrease starts, as is the case in downtown Los Angeles. Overall, a

55% reduction in demand produces approximately a 90% reduction in traffic delay. Although not as dramatic as the delay reductions, the vehicle emissions and fuel consumption levels all decrease linearly at a larger rate compared to the demand change. Specifically, a 55% reduction in traffic demand typically generates a 65% reduction in vehicle emissions and fuel consumption levels.

Regarding the impact of the transportation network features on these variables, we conclude that downtown networks comprised of more local streets more sensitive to the initial demand reduction (5% and less). Specifically, the downtown LA network shows a more dramatic initial reduction in vehicle delays when the traffic demand starts to drop (a 5% reduction in the traffic demand produces a 18.5% reduction in vehicular delay for LA vs. an 11% reduction for the I-66 corridor). However, the reduction in delays after the initial 5% reduction are more significant for the I-66 corridor. In summary, it appears that the network layout has a limited influence on the reductions in vehicle fuel consumption and emission levels and a more noticeable impact on delay reductions. Further investigations are warranted to establish generalizable conclusions.

The findings of this study suggest that policy makers should consider measures to limit the number of vehicles on roads and suppress overall demand levels after the pandemic subsides by increasing teleworking, car-pooling, increasing the usage of public transit, as well as using new technologies such as mobility credits (Fujii, Gärling, and Kitamura 2001; Moser, Blumer, and Hille 2018; Hai Yang and Wang 2011) to incentivize travels to reduce their travel needs. Such changes in travel behavior will have substantial benefits on the transportation system.

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