The Impacts of Connected Vehicles on Fuel Consumption, and Traffic Operation under Recurring and Nonrecurring Congestion

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ABSTRACT

Communication technology enables information transmissions among vehicles and has the potential to improve the transportation system performance. The goal of the current study is to evaluate the effectiveness of a congestion warning application in connected vehicles on improving mobility and reducing fuel consumption at the network level. A microsimulation model of east part of El Paso, Texas was created in the study. The impacts of connectivity at different market penetration rates (MPRs) were evaluated. Two scenarios including rerouting based on the shortest travel time and the lowest fuel consumption were implemented in case of recurring and non-recurring congestion. The results of the study demonstrated the effectiveness of the connected vehicle technology in the network level traffic operation and fuel consumption. Surprisingly, rerouting based on the least fuel consumption was found to be more effective in reducing both the overall travel time and fuel consumption.

Keywords: Connected vehicles; Emission; Fuel consumption; Rerouting.
INTRODUCTION

Connected vehicle technology enables communication and information transmissions among vehicles and infrastructure and has the potential to improve mobility, safety, and emissions from the transportation system. More efficient management of traffic by transferring real-time information for selecting a route, warning messages generated by surrounding vehicles around for reducing collisions, and less congestion are some examples of potential connectivity benefits that can improve the performance of the transportation system.

The impacts of communication technology and rerouting strategies on travel time were evaluated in many studies. Guidance strategies in a connected environment were assessed using a VISSIM microsimulation model on a small hypothetical network (Lee and Park 2008). The result of the research demonstrated the effectiveness of the routing guidance strategies in reducing travel time. Oh and Jayakrishnan investigated the impacts of advanced traveler information system (ATIS) on travel time using a simulation model. Their study demonstrated that average network travel time was reduced by 25% when 40% of drivers received real-time traffic information (Oh and Jayakrishnan 2002). Kattan et al. evaluated the impacts of V2V technology on non-recurring congestion (Kattan et al. 2012). They developed two application programming interfaces (API) for simulating incidents and warning drivers of incidents to increase their awareness and reduce their aggressiveness. They then evaluated the impacts of congestion level and market penetration rate (MPR) on travel time savings. Their study demonstrated the effectiveness of connected vehicles in improving safety and reducing travel time for moderate and high congestion level. Paikari et al. assessed the impacts of advisory speed and rerouting guidance on urban freeways using a microsimulation model called Paramics. According to their study for MPR of 50%, the travel time on the main corridor is improved by 30% to 40% (Paikari et al. 2013, 2014). Olia et al. investigated the impacts of en-route decisions by transferring real-time information from mobility, safety, and environmental perspectives at the network level (Olia et al. 2015). They assumed that non-connected vehicles also reroute in response to visible congestion or other sources of information. Their study demonstrated a significant potential of connected vehicles on network performance.

The contributions of the current study are: (1) the network-wide evaluation of connected vehicles on traffic operation and fuel consumption in recurring and non-recurring congestion, and (2) comparison of two rerouting scenarios including rerouting based on least travel time and rerouting based on least fuel consumption.

OBJECTIVES

The objectives of the current study are: 1) evaluation of the mobility and environmental impacts of a congestion warning application on connected vehicles under recurring and nonrecurring congestion and 2) comparison of two rerouting scenarios including rerouting based on minimizing (a) travel time and (b) fuel consumption on network performance.
METHODOLOGY

Simulation model

To examine the congestion warning application of communication technology, a microsimulation model was developed. For this purpose, the network of El Paso in Texas was selected for several reasons. First, this area is congested. Second, it encompasses different types of roads including freeway, arterial, and minor streets which provides a more general view of the network evaluation of connected vehicles. More importantly, this area is in a non-attainment area and evaluation of the current conditions on the network is helpful for future decisions to reduce emissions. Simulation of Urban Mobility (SUMO) was used along with Traffic Control Interface (TraCI) to develop the algorithms in the study. SUMO is an open source traffic simulation package which helps in investigating different research objectives (Behrisch et al. 2011; Krajzewicz et al. 2002, 2006, 2012). This system of applications has a broad spectrum of functionalities. Most of the features are still under research to adapt to the future of the transportation system. Being open source provides this opportunity for traffic simulation community to develop new algorithms and expand the functionality of the tools.

The network of El Paso was modeled in SUMO. For this study, we examined morning peak period (6 am to 8 am). Future analysis will examine the entire day of traffic. The choice of morning peak or evening peak may not affect our studies. However, since recurrent congestion, which is happening in the morning or evening, is one of the problematic part in traffic management, we focused on this time of day.

The simulated network is shown in Figure 1. The freeway, I-10, with its frontage road, is located in the southern part of the network and is one of the most congested parts of the network. Montana avenue located in the northern part of the network is one of the most congested arterials in El Paso during the peak period. Many local roads in between provide connections between I-10 and major arterials, so we could test the rerouting from I-10 due to a simulated crash on I-10.

![Figure 1. Simulated network with boundaries](image-url)
Data
The origin-destination (OD) data provided by Texas A&M Transportation Institute El Paso office was used in the study. To convert the trip data which shows the Origin link, destination link and the departure time to the vehicles routes, a developed dynamic traffic assignment model in SUMO (DuaIterate) was used. The DuaIterate application of SUMO is an iterative process to find the shortest path based on the updated cost function. The model was simulated and the link counts was exported from the simulation model. The link volumes were then compared with the volume data provided by Texas Department of Transportation. Then the vehicle volumes were adjusted based on this information. This process has been repeated until the desired accuracy were achieved. The information of the network flow, density and traffic operation of the network were reported in (Samimi Abianeh et al. 2018).

Congestion warning algorithm
In order to quantify the impacts of a congestion warning application, an algorithm was developed to inform drivers of vehicles with communication technology of significant congestions on the links ahead of them. First, the network links ahead of the vehicles were examined to find if there was congestion and its location. The next step is to run the rerouting scenario based on the objectives and assumptions. For the first step, the level of congestion is evaluated based on the average speed on the links of the network. If the average speed is lower than a percentage of the speed limit, the link was marked as congested. After determining the congested links, the next step was to examine the vehicles routes. For the regular vehicles, we assumed that they continue to use the assigned routes and they will not change their routes during their trip. For the connected vehicles, they will continue using the assigned routes until they get warning of the congestion on the links ahead of them. Since the traveler’s behavior is different from one driver to another driver, a probability function was used to simulate traveler’s willingness to change their route in response to the received information (Jeihani and Ardeshiri 2013). Since drivers behave randomly in response to congestion and random in nature follows Normal distribution, we assume that the compliance rate follows Normal distribution (equation1).

\[ \text{Compliance rate} = \alpha \times \exp \left( \frac{-n^2}{2\sigma^2} \right) \]

(1)

Where \( \alpha \) is a constant to adjust the probability function, \( n \) is the number of rerouted vehicles due to congestion on each link, and \( \sigma \) is the standard deviation of the normal distribution. In the current study, we assumed different values of \( \alpha \) based on the location of the vehicles. For example, vehicles on the inner lanes of the freeway are less likely to use the exit lane to change their route. Moreover, as the number of rerouted vehicles increases the probability of rerouting decreases at each location (Figure 3). A random value will then be generated for each vehicle and compared with the compliance rate calculated by the probability function to determine whether the vehicle will change its route.

Two rerouting scenarios were examined. For the first scenario, the alternate route is the one with the shortest average travel time during the last time step. In the
second scenario, the alternate route is the one with the least fuel consumption over the last time step.

**Figure 2. Rerouting Algorithm**

**Modeling of regular and connected vehicles**

Two car-following models were employed in our study. The first model is the modified version of Krauss model which is the default car following model in SUMO. This was used for non-connected vehicles. The assumption on this car following model is to make a collision-free system (Krauß 1998). Therefore, travelers always drive at the speed which is not higher than the safe speed.
The Intelligent Driver Model (IDM) was incorporated to simulate the behavior of connected vehicles. IDM, which is a deterministic car-following model developed by Treiber et al., enhances realistic properties of traffic dynamics comparing to the previously developed deterministic models such as Gipps model (Treiber et al. 2000). Connected vehicles enable drivers to receive and send real-time information which helps travelers to have a better understanding of the events in their surroundings. As it was suggested in the literature, IDM is capable of simulating the behavior of connected vehicles (Talebpour and Mahmassani 2015). The equations employed for estimating the acceleration in IDM are as follows:

**Fuel consumption model**

The Virginia Tech Comprehensive Power-based Fuel Consumption Model (Rakha et al. 2003, 2011) which was used in this study estimates fuel consumptions and CO₂ production using the trajectory data and some estimated parameters based on the vehicle’s features. This model has the advantage of not switching abruptly between two states of fuel consumption and zero consumption without any middle ground. Moreover, calibrating the parameters based on the vehicles feature enhances the accuracy of the model. Toyota Camry 2012 was considered as the typical vehicle for model calibration because it was reported as the bestselling car (“Experian Automotive: Midrange Cars are Top-Selling Segment; Toyota Camry Top Vehicle - Experian Global News Blog” 2012)

**NUMERICAL RESULTS**

The results of the simulation model created in SUMO of the network of El Paso, Texas are presented in this section. The traffic demand was obtained from the origin-destination matrix provided by Texas A&M Transportation Institute and calibrated using the traffic count data provided by Texas Department of Transportation (TxDOT). The model was simulated for two hours in the morning peak (6 AM to 8 AM). Six scenarios for the market penetration rates (MPR) including 0, 20, 40, 60, 80, 100% of connectivity were modeled in the study. An incident was generated using TraCI on the

Figure 3. Distribution of traveler’s behavior in response to congestion warning
westbound of I-10 during the simulation. The duration of incident generated is 15 minutes.

Two algorithms were developed for rerouting. In the first algorithm, the en-route decision is made by finding the shortest path based on the travel time using the real travel time data (travel time from last time step). In the second algorithm, the shortest path is based on minimizing the fuel consumption using the average fuel consumption on the links at the last time step.

Table 1 and Table 2 show the total network-wide travel time and fuel consumption for two methods of rerouting based on travel time and fuel consumption for recurring and non-recurring congestion. These tables demonstrate that connected vehicle technology improves both traffic operation and fuel consumption. The percentages of the reduction in travel time and fuel consumption for each MPR are shown in Table 3 and Table 4. Using either least travel time path or least fuel consumption route for en-route decisions results in reducing the total travel time and fuel consumption over the network. By rerouting based on the least travel time for the model without an incident, a reduction of 12% in total network travel time based on 60% connectivity was observed. After 60% of connectivity, likely since the algorithm used to reroute trips decreases the percentage of deviated trips based on a function for compliance rate the changes gets very small. The highest reduction in fuel consumption due to the connectivity was about 25%. Similarly, Modeling based on minimizing fuel consumption the observed reduction for travel time was about 15% at MPR of 60% and 27% of fuel consumption at MPR of 100%.

In the case of having an incident during the simulation, even greater reductions in travel time and fuel consumption were observed. Based on the results demonstrated in Table 4, by implementing the least travel time method for rerouting, there was a 14% reduction in the network travel time for a 60% MPR. After 60% MPR, a slight increase in the total travel time (less than 1%) was observed. This increase might be due to the rerouting of so many vehicles to alternative routes that the alternate routes become slower. Additionally, since vehicles are rerouted to signalized arterials, some of the rerouted vehicles may encounter more signal delay than expected. A 26% of decrease in fuel consumption was observed for 100% connectivity. In general, as the MPR increases the rate of reduction in travel time and fuel consumption decreases. Using the model based on minimizing fuel consumption, the highest reduction in travel time was around 17% and the reduction in fuel consumption was 29% at 100% of connectivity.

Table 1. Average Travel time and fuel consumption for two methods of rerouting including minimum travel time and minimum fuel consumption (Total number of vehicles = 53320)

<table>
<thead>
<tr>
<th>Rerouting method</th>
<th>Rerouting Based on Travel Time</th>
<th>Rerouting based on Fuel consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>MPR</td>
<td>Time(min)/vehicle</td>
<td>Fuel consumption (ml)/vehicle</td>
</tr>
<tr>
<td>0%</td>
<td>8.2</td>
<td>226.7</td>
</tr>
<tr>
<td>20%</td>
<td>7.8</td>
<td>210.8</td>
</tr>
</tbody>
</table>
Table 2. Total Travel time and fuel consumption for two methods of rerouting including minimum travel time and minimum fuel consumption (for the model with an incident) (Total number of vehicles = 53320)

<table>
<thead>
<tr>
<th>Rerouting method</th>
<th>Rerouting Based on Travel Time</th>
<th>Rerouting based on Fuel consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time(min)/vehicle</td>
<td>Fuel consumption (ml)/vehicle</td>
</tr>
<tr>
<td>0%</td>
<td>8.4</td>
<td>230.3</td>
</tr>
<tr>
<td>20%</td>
<td>7.9</td>
<td>211.9</td>
</tr>
<tr>
<td>40%</td>
<td>7.5</td>
<td>196.4</td>
</tr>
<tr>
<td>60%</td>
<td>7.2</td>
<td>181.4</td>
</tr>
<tr>
<td>80%</td>
<td>7.2</td>
<td>175.9</td>
</tr>
<tr>
<td>100%</td>
<td>7.3</td>
<td>170.2</td>
</tr>
</tbody>
</table>

Table 3 and Table 4 also demonstrate the comparison between two methods of rerouting. As it can be observed from the tables, the second method which is the rerouting based on the least fuel consumption has better performances in both network travel time and network fuel consumption. The maximum difference between these two methods is at most about 4 percent for total travel time and total fuel consumption in both recurring and non-recurring congestion.

Table 3. Change in Travel time and Fuel Use for different MPR compared to the base case (0% connectivity)

<table>
<thead>
<tr>
<th>Rerouting method</th>
<th>% Reduction for Rerouting Based on Travel Time</th>
<th>% Reduction for Rerouting based on Fuel consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time(hours)</td>
<td>Fuel consumption (L)</td>
</tr>
<tr>
<td>20%</td>
<td>4.8%</td>
<td>7.0%</td>
</tr>
<tr>
<td>40%</td>
<td>9.9%</td>
<td>14.8%</td>
</tr>
<tr>
<td>60%</td>
<td>12.2%</td>
<td>20.1%</td>
</tr>
<tr>
<td>80%</td>
<td>11.6%</td>
<td>22.0%</td>
</tr>
<tr>
<td>100%</td>
<td>11.4%</td>
<td>24.9%</td>
</tr>
</tbody>
</table>
Table 4. Change in Travel time and Fuel Use for different MPR compared to the base case (0% connectivity) for the model with incident

<table>
<thead>
<tr>
<th>Rerouting method</th>
<th>% Reduction for Rerouting Based on Travel Time</th>
<th>% Reduction for Rerouting based on Fuel consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time(hours)</td>
<td>Fuel consumption (L)</td>
</tr>
<tr>
<td>20%</td>
<td>6.2%</td>
<td>8.0%</td>
</tr>
<tr>
<td>40%</td>
<td>10.3%</td>
<td>14.7%</td>
</tr>
<tr>
<td>60%</td>
<td>14.0%</td>
<td>21.2%</td>
</tr>
<tr>
<td>80%</td>
<td>14.0%</td>
<td>23.6%</td>
</tr>
<tr>
<td>100%</td>
<td>13.3%</td>
<td>26.1%</td>
</tr>
</tbody>
</table>

SUMMARY

Connected vehicle technology enables real-time traffic data exchange among vehicles, infrastructure, and passenger devices and can help travelers to make better travel decisions. In the current study the effectiveness of a congestion warning for connected vehicles on reducing travel time, and fuel consumption was modeled. A microsimulation model of El Paso, Texas road network was created in SUMO. The model was run for different MPR of connected vehicles. Two scenarios for rerouting were examined. The first scenario rerouted based on minimizing travel time. The second scenario rerouted based on the path with the least fuel consumption. An incident was also generated using TraCI during the simulation. The impacts of connectivity on travel time and fuel consumption were evaluated for both recurring and non-recurring congestion. The results of the study demonstrated the fuel consumption reduction of up to 24% using the first scenario of rerouting and 27% using the second scenario of rerouting in a nonrecurring congestion. From the traffic operation perspective, the travel time was reduced by about 12% using the first method of rerouting and 15% using the second method of rerouting. Higher differences were observed in the case of non-recurring congestion. Future research is needed to investigate travelers’ response to a congestion warning. Moreover, more research is needed to evaluate the optimization method for rerouting instead of just using real-time traffic information for en-route decision making. Since in this study, we just evaluated passenger cars (and for fuel use only one type of car), other vehicle types like heavy duty vehicles can also be added to the vehicle fleet mix for future investigation.

ACKNOWLEDGEMENT

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