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A Framework for Smart Freight Mobility with Crowdsourcing

Shailesh Chandra[a,]*, R. Thirumaleswara Naik[b], Jose Jimenez[a]

[a]California State University, Long Beach, California, U.S.A, 90803
[b]Indian Institute of Science, Bengaluru, India - 560012

Abstract

In this paper, crowdsourcing is used to improve operations of freight truck. The goal is to improve the efficiency of freight in being to detour when an unforeseen downstream congestion occurs on its path. This is defined as one of the features of a 'smart freight' truck. The detour is achieved by having access to crowdsourced data of an imminent congestion on its route. In this paper, a discrete-time Markov chain (DTMC) model is developed to develop an efficiency improvement model. Example using ramp exit 24 off interstate 405 (I-405) and I-605 in the Southern California Region show improvements in freight truck efficiencies for the detour. It is observed that almost 33% of freight trucks subscribed to crowdsourced information could use the ramp exit to avoid downstream congestion. Finally, formulation for probability mass function is also presented which can be used within traffic simulation software packages to enhance both passenger and truck freight operations using crowdsourcing

Keywords: Keywords: crowdsourcing; smart freight; routing; mobility; exit ramp; congestion;

1. Introduction and Background

Smart Freight Mobility has been the research spotlight under a joint modal 'Smart Roadside' program between the FHWA and Federal Motor Carrier Safety Administration (FMCSA) (Smart Roadside, 2017). The program encompasses technologies for enhanced roadside condition and traffic information-sharing with commercial vehicle for route planning and improved access to intermodal ports, urban pick-up, and delivery locations that are crucial to the missions of the U.S. Department of Transportation (USDOT). The vision underlined under this program is one in which commercial vehicles, highway facilities, enforcement resources, intermodal facilities, and other modes on the

* Corresponding author. Tel.: +1-562-985-4654; fax: +1-562-985-2380.
E-mail address: shailesh.chandra@csulb.edu

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transportation system collect and share data seamlessly in order to improve freight's operational efficiency and mobility – which this proposed research identifies as the "smart freight". In this paper, the technique of crowdsourcing information on downstream congestion information is explored to develop efficient smart freight operations.

Crowdsourcing is emerging as a powerful tool in providing possible solutions to problems that are traditionally expensive to solve due to immense data collection needs (Brabham D.C., 2008; Chatzimilioudis G., 2012; Gao H., 2011). Other possible avenues in which crowdsourcing can be of great use could include smart parking, ridership data, transit troubleshooting, road condition monitoring and assessment, urban traffic planning and management, and many other issues involving big data (Ferster et al., 2017; Wang et al., 2016; Zheng et al., 2016; Sun et al., 2017). Crowdsourced data primarily comes from social media, however, in a raw format which need to be optimized in collection and dissemination for understanding the traveling public. With no roadway infrastructure needed for data collection in crowdsourcing, the technology is considered to be one of the top trends by Transportation Management Centers (TMCs) for coordinating their responses to traffic congestion and incidents in real time (Mizuta et. al, 2013). The role of social media and crowdsourcing in transportation applications is rapidly evolving (Misra et. al., 2014, Ali et. al, 2012). Some states, including California, are already utilizing transportation-related crowdsourced data, anonymous in nature, to provide information to citizens and drivers about road conditions, congestion and closures under the Connected Citizen's Program (Caltrans Press Release, 2017). This two-way real-time information sharing about California's roadways provided by Caltrans' QuickMap gives drivers more power to plan their commutes and trips (Caltrans' QuickMap, 2017). With an increased use of crowdsourced data for transport applications, this proposed research is a step towards leveraging crowdsourcing technology to the development of a smart freight system.

2. Methodology

2.1. Defining States

This component of research consists of developing states for DTMC mimicking truck manoeuvres close to an exit ramp. The derivation is based on the model developed by Chandra et al., (2019). The states developed in this proposed research account for various traffic conditions of the road (such as existing speed, density, delay etc.) and particularly applicable for freight trucks. The set-up is shown in Fig. 1 and presents the skeleton of the modelling framework.

In the sketch of Fig. 1, it is conveyed that only those vehicles which receive information that are obtained through crowdsourcing benefit from deviations from the usual route. This is because the information about the downstream congestion is provided much before to facilitate use of the improved route by the freight vehicles via the ramp exits. It is assumed that other vehicles that do not have access to the crowdsourced information will continue to proceed towards the congested point.

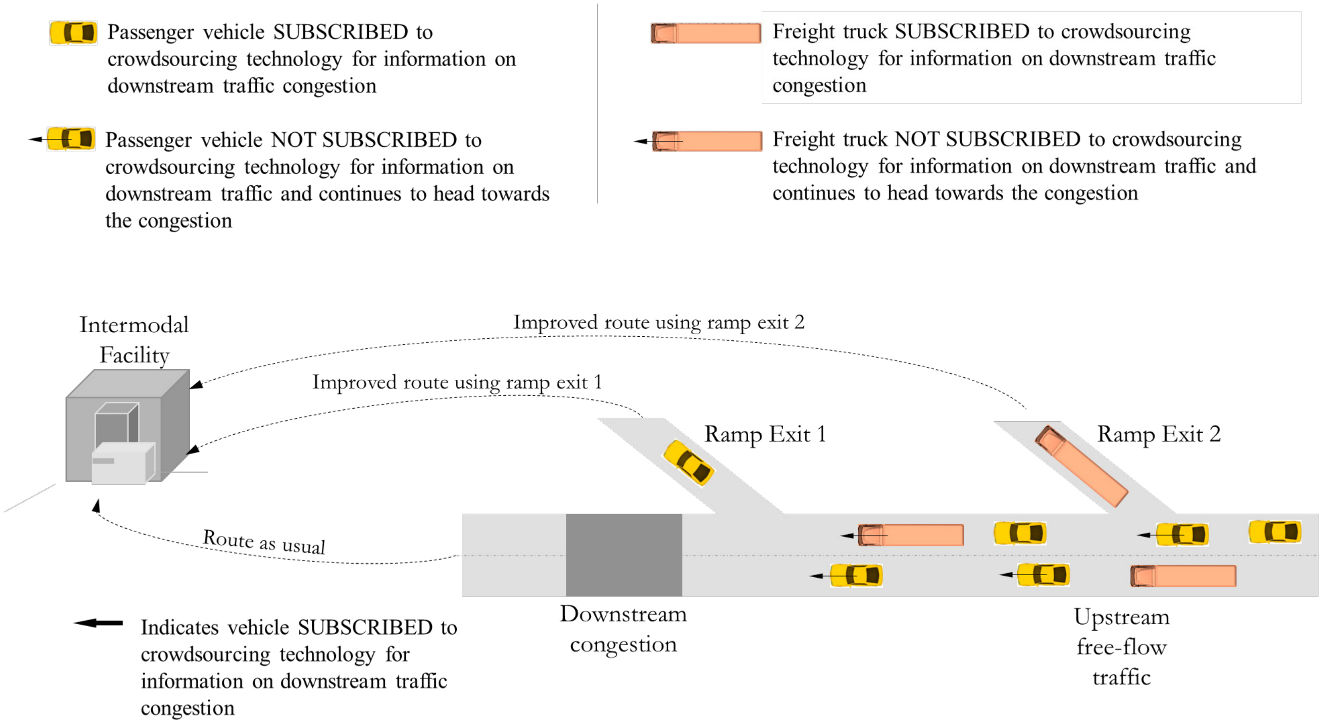

Fig.1. Model set-up for traffic operation on a freeway (Chandra et al., 2019)

The skeletal of the set-up shown in Fig. 1 is developed in Fig. 2 – with the following details as follows:

1. The area around the ramp exit is divided into seven zones for the two lanes, and
2. The length of each zone is fixed (typically175-ft equivalent to 2-second headway for speed limit of 60 mph on the freeway). Thus, each zone will have at most only one vehicle (passenger car or truck) or none across all the seven zones at any given instant of time.

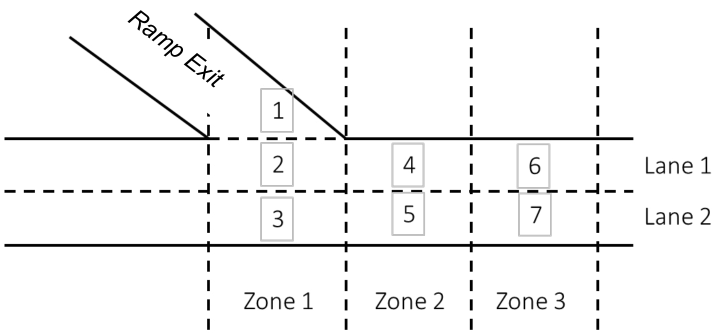

Fig. 2. Simplified representation of the area around exit ramps.

3. The movement of freight trucks across the six zone-lane pairs with one exit ramp case for the seven slots shown in Fig. 2. occur with a series of well-defined probabilities as explained below:

i. $P_{V,1,3}$ = Probability of arrival of a vehicle (freight or passenger) at *Lane 1 – Zone 3*. The reference is made to zone with slot labelled *6*.

ii. $P_{V,2,3}$ = Probability of arrival of a vehicle (freight or passenger) at *Lane 2 – Zone 3*. The reference is made to zone with slot labelled *7*.

iii. $P_{MF,1,2}$ = Probability of moving forward of a vehicle (freight or passenger) from *Lane 1 – Zone 3* to *Lane 1 – Zone 2*. The reference is made to zone with slot labelled *4*.

iv. $P_{MF,1,1}$ = Probability of moving forward of a vehicle (freight or passenger) from *Lane 1 – Zone 2* to *Lane 1 – Zone 1*. The reference is made to zone with slot labelled *2*.

v. $P_{MF,2,2}$ = Probability of moving forward of a vehicle (freight or passenger) from *Lane 2 – Zone 3* to *Lane 2 – Zone 2*. The reference is made to zone with slot labelled *5*.

vi. $P_{MF,2,1}$ = Probability of moving forward of a vehicle (freight or passenger) from *Lane 2 – Zone 2* to *Lane 2 – Zone 1*. The reference is made to zone with slot labelled *3*.

vii. $P_{MF,R}$ = Probability of moving forward of a vehicle (freight or passenger) from *Lane 1 – Zone 2* to *Ramp Exit.* The reference is made to zone with slot labelled *1*.

viii. $P_{LC,1,1}$ = Probability of lane changing of a vehicle (freight or passenger) from *Lane 2 – Zone 2* to *Lane 1 – Zone 1*.

ix. $P_{LC,2,1}$ = Probability of lane changing of a vehicle (freight or passenger) from *Lane 1 – Zone 2* to *Lane 2 – Zone 1*.

x. $P_{LC,1,2}$ = Probability of lane changing of a vehicle (freight or passenger) from *Lane 2 – Zone 3* to *Lane 1 – Zone 2*.

xi. $P_{LC,2,2}$ = Probability of lane changing of a vehicle (freight or passenger) from *Lane 1 – Zone 3* to *Lane 2 – Zone 2*.

There is a total of 3^7 states (= 2187 states) possible for the DTMC being studied based on the above manoeuvres. The product of the following probabilities for each transition of the DTMC from one state to another yields a next feasible state with every new transition. Thus, the probability, ρ, to be evaluated for possible transition to the next state is given by:

$$\rho = P_{V,1,3} \times P_{V,2,3} \times P_{MF,1,1} \times P_{MF,1,2} \times P_{MF,2,2} \times P_{MF,2,1} \times P_{MF,R} \times P_{LC,1,1} \times P_{LC,2,1} \times P_{LC,1,2} \times P_{LC,2,2} \quad (5)$$

Let the probability of recurring congestion be represented by P_{RC} and define $S_n(i) = P_{RC}$ indicating the recurring congestion occurs after n^{th} time interval with initial state $X_0 = i$. The formulation by Evans et al. (2001) is used to summarize the probability of recurring congestion based on conditional probability for various scenarios for $n \geq 2$. This is shown in Table 1.

Table 1. Summary of probability expressions based on initial states

Condition	Probability Expression, $S_{n+1}(i) =$
$i \in G$	$\sum_{j} S_n(j)\, p_{ij}$
$i \in B, j \in G$	$\sum_{k} S_{n-1}(k)\, p_{jk}$
$i \in B, j \in B, k \in G$	$\sum_{l} S_{n-2}(l)\, p_{kl}$
$i \in B, j \in B, k \in B$	0

On rewriting the final expression for $S_{n+1}(i)$ based on the conditions identified in Table 1, we get

$$S_{n+1}(i) = \begin{cases} \sum_{j} S_n(j)\, p_{ij} & \text{if } i \in G, \\ \sum_{j \in G}\left(\sum_{k} S_{n-1}(k) p_{jk}\right) p_{ij} + \sum_{k \in G}\sum_{j \in B}\left(\sum_{l} S_{n-2}(l) p_{kl}\right) p_{ij}\, p_{jk} & \text{if } i \in B \end{cases} \tag{1}$$

Assuming that the situation for recurring congestion arises only after the 2nd time interval, we have

$$S_0(i) = 1 \forall i, \tag{2}$$

$$S_1(i) = 1 \forall i, \tag{3}$$

and

$$S_2(i) = \begin{cases} 1 & \text{if } i \in G, \\ 1 - \sum_{j \in B} p_{ij}^2 & \text{if } i \in B \end{cases} \tag{4}$$

Therefore, with Eqs. (1) - (4), the probability that freight vehicles positioned with an initial state i will continue to move along the freeway towards the congested location at n^{th} time interval with probability $f_n(i) = \left\{S_{n-1}(i) - S_n(i)\right\}$. This occurs after three or more consecutive bad states for the positions of the vehicles arranged in the seven slots of the lane-zone pairs. This also indicates that in order for the freight trucks not to intensify congestion, the probability of exiting the ramp before the n^{th} time interval (and no three consecutive bad states have occurred) is $F_n(i) = \sum_{m=1}^{n-1}\left\{S_{m-1}(i) - S_m(i)\right\}$. Simple plot of probability $F_n(i)$ with various time intervals can help determine the time around which freight trucks can be detour via the exit ramp based on crowdsourced information on downstream congestion.

3. Application Example

An example application of the DTMC model developed in this research is carried out using simulation exercise for the exit ramp at San Diego Fwy (I-405 N) and I-605 N in the Southern California Region. Data for truck traffic volume are obtained from Caltrans. The set-up used for carrying out the simulation is shown in Fig. 3. Each zone has a length of 175-ft which is equivalent to 2-second headway for speed limit of 60 mph on the freeway. The probability inputs for the simulation are compiled in Table 2.

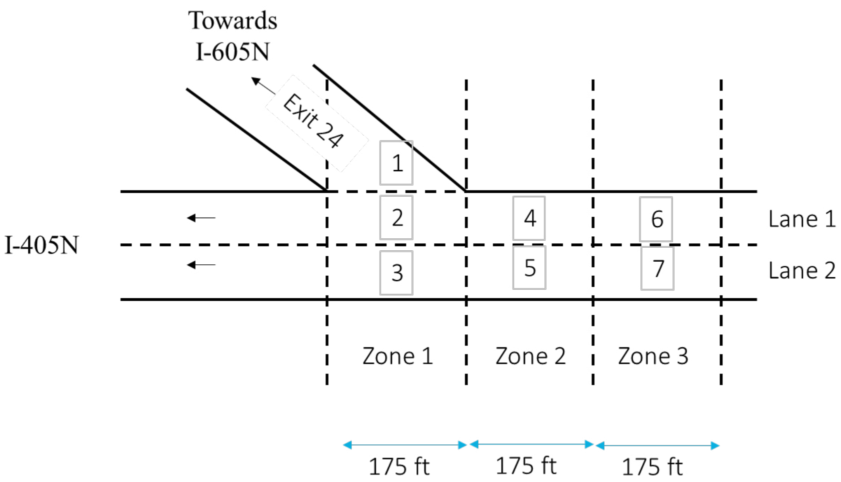

Fig. 3. Set-up for simulation exercise

Table 2. Probability values used for the DTMC model

Probability	Value(s)
$P_{V,1,3}$	Arrival Rates for Lane1-Zone 1: 1800 veh/hr (free flow scenario) and 900 veh/hr (congested scenario)
$P_{V,2,3}$	Arrival Rates for Lane1-Zone 1: 1800 veh/hr (free flow scenario) and 900 veh/hr (congested scenario)
$P_{MF,1,1}$, $P_{MF,1,2}$, $P_{MF,2,1}$, $P_{MF,2,2}$, and $P_{MF,R}$	1 (assuming that a vehicle is not stalled in any lane-zone pair)
$P_{LC,1,1}$, $P_{LC,1,2}$, $P_{LC,2,1}$, and $P_{LC,2,2}$	0 (denotes lane change is not allowed) and 1 (denotes lane change is enforced). The probability $P_{LC,1,1}$ and $P_{LC,2,1}$, are complementary to each other as the lane change from lane 1 – zone 2 to lane 2 – zone 1 and lane change from lane 2 – zone 2 to lane 1 – zone 1 cannot occur simultaneously, as this can create collision situation for two vehicles. Similarly, $P_{LC,1,2}$, and $P_{LC,2,2}$ are also complementary to each other because of the above reasons for lane changes occurring from lane 1 – zone 2 to lane 2 – zone 2, and vice-versa. Therefore, $P_{LC,1,1} = (1 - P_{LC,2,1})$ and $P_{LC,1,2} = (1 - P_{LC,2,2})$

3.1. Results

Observation times for the simulation output are assumed to vary from 5 minutes to 30 minutes with an increment of 5-minute interval. Both free-flow conditions and congested situations are analysed separately. The traffic speed in the lane-zone pairs constructed for the I-405 & I-605 DTMC model for simulation are assumed to be 60 mph for the free-flow situation and 30 mph for the congested situation. There are hundred replications (considered to be large enough) for each simulation setting.

Simulation results for the DTMC model built in this research show that with crowdsourced information about the downstream traffic congestion, an increased number of freight trucks would be able to exit the ramp for I-605 and find alternate routes with the exit to reach to the destination. The output result for the free-flow traffic is shown in Fig. 12 which indicates an increasing trend in the number of freight trucks (which are subscribed to crowdsourced information about downstream traffic congestion) and the simulation observation times. It is noted that for the simulation with 5 min, 10 min, 15 min, 20 min, 25 min and 30 min time intervals, the count of freight trucks which had information about the downstream traffic congestion and used the ramp exit were 3393, 6785, 10176, 13419, 16788 and 20142, respectively. The total number vehicles (both passenger and freight) that entered the lane-zone pairs were 10095, 20288, 30406, 40461, 50488 and 60568, respectively. For congested traffic situations, the number of trucks exiting the ramp reduced to 5694, 11453, 17291, 23275, 28139 and 35647 for 5 min, 10 min, 15 min, 20 min, 25 min and 30 min time intervals, respectively. Thus, on an average, almost 33% of total vehicles (passenger and freight trucks) which are freight trucks subscribed to crowdsourcing information could use the ramp exit to avoid downstream congestion. This is applicable for both when the traffic within the lane-zone pair is free flow or congested. It was observed that approximately 16% of vehicles which are freight trucks and subscribed to crowdsourced information on downstream congestion could not make it through the ramp exit. The reason was due to limitations in lane change movements of these freight trucks. The percentage of freight trucks which could not exit the ramp increased from 16% to almost 50% without any subscription to crowdsourced information about the downstream congestion. This was expected since there was no subscription of trucks to avoid progressing towards the congested point of the freeway.

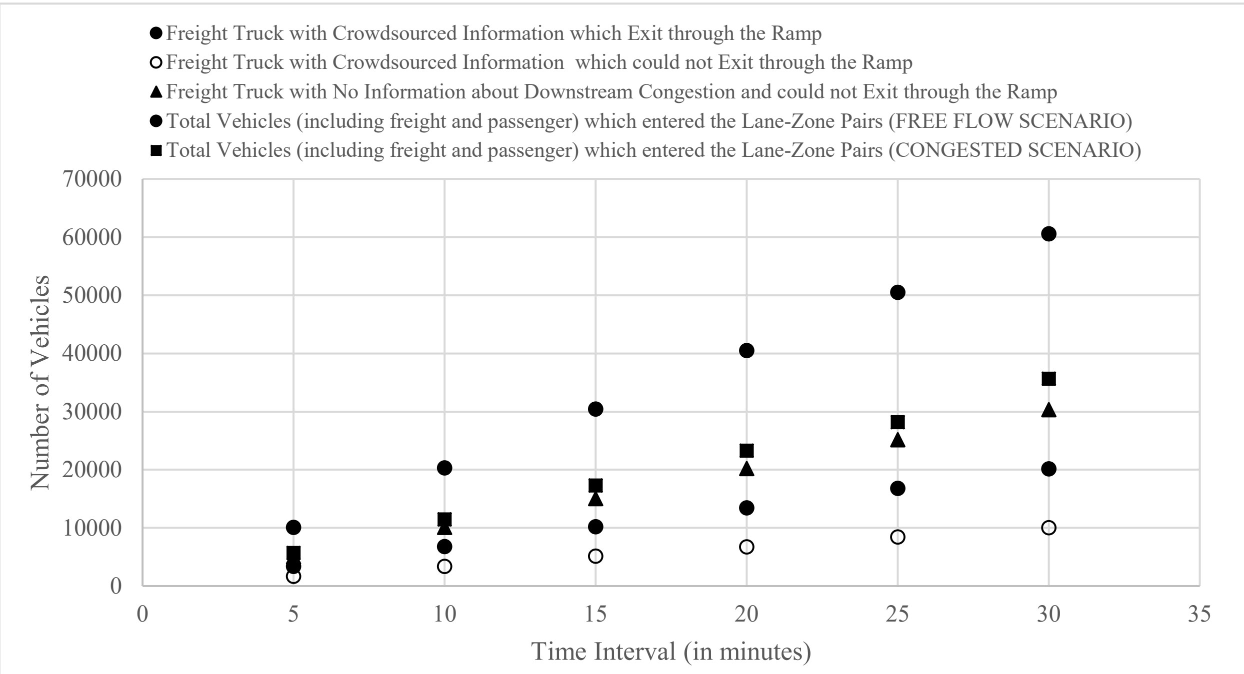

Fig. 4. Simulation results indicating improvement in freight truck routing with crowdsourced information

4. Concluding Remarks

This research involves developing stochastic model(s) based on Markov chains. Markov chains have wide applications in freeway traffic congestions. The model developed in this proposed research is sensitive to traffic conditions (such as existing speed, density etc.). The model will be applicable for freight trucks and can be used to indicate the duration of congestion for a stop-and-go traffic situation on the highway. The vehicle (whether a passenger car or freight truck) subscribed to crowdsourced information about real-time traffic situation on the highway will have the advantage to use ramp exits and find better routes if there is one to avoid an immediate downstream congestion. Alternately, this means that vehicles that do not have access to the crowdsourced information will continue to proceed towards the congested point.

The set-up used in the modelling framework requires input data that are real-time crowdsourced data on traffic situations and freight data related to commodity flow, truck tonnage, etc. Results show that almost 33% of total vehicles (passenger and freight trucks) which are freight trucks subscribed to crowdsourcing information can successfully use the ramp exit to avoid downstream congestion. This output from the model developed in this research can be subsequently used to estimate savings in fuel consumption per mile and increase in freight tonnage to establish efficiency improvements in operations and mobility of smart freight.

Analysis carried out with both average daily passenger cars and truck traffic volumes close to ramp exit 24 of interstate 405 (I-405) and leading to I-605 in the Southern California Region, substantiate the effectiveness of the model. DTMC analysis shows that almost 33% of total vehicles (passenger and freight trucks) which are freight trucks only that are subscribed to crowdsourced information, could use the ramp exit to avoid downstream congestion. Finally, formulation for probability mass function is also presented which can be used within traffic simulation software packages to enhance both passenger and truck freight operations using crowdsourcing.

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