METRANS

Investigating Impact of Crowdsourcing on Smart Freight Mobility

Final Report

Shailesh Chandra, Ph.D.
Jose Jimenez
Annie Nguyen

Department of Civil Engineering and Construction Engineering Management
California State University, Long Beach

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Introduction and Background

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). Crowdsourcing refers to the technique of gathering opinions and information from the crowd to "find solutions which otherwise would be hard or impossible to resolve" (Ali et. al, 2012). Therefore, when used effectively, crowdsourcing can use the public's intelligence and skills to solve complex issues (Nurdden et. al, 2007; Magtoto et. al, 2012; Misra et. al, 2014). The collection of information through crowdsourcing is often facilitated by social media platforms such as Twitter, Facebook etc. (Alvaro et. al, 2015). There are different types of crowdsourcing for different tasks for example; crowdfunding, crowdsourcing design, microtasks etc. The phrase crowdsourcing was "framed by Jeff Howe in the computer magazine Wired where crowdsourcing for him meant "the new pool of cheap labor: everyday people using their spare resources to create content, solve problems" (Nurdden et. al, 2007; Howe, 2006). As worded in Crowdsourcing Week, "Crowdsourcing is the practice of engaging a 'crowd' or group for a common goal often innovation, problem solving, or efficiency, powered by new technologies, social media and web" (Brabham, 2008) which is the same definition from google and any other website only phrased differently. Currently, in both the fields of Intelligent Transportation Systems (ITS) and traffic research, the possible uses for crowdsourcing has begun to receive attention (Santani et. al, 2015; Ali et. al, 2012; Juhlin, 2010; Ostergren M., 2005). 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).

With the advent of Big Data, mobile applications related to traffic information and communications technologies have seen a surge, however, with missing developments in artificial intelligence needed to cause forward looking solutions to smart freight needs (Langer and Vaidyanathan, 2014). Social media and mobile applications provide valuable platform for state DOTs in collection and sharing real time data on traffic congestion, incidents and weather impacts (Adler et. al., 2014). Real time data-sharing and collection is made possible due to the "crowdsourcing" nature of social media - which a recently published Federal Highway

Administration (FHWA) report cites as an emerging strategy to address the gap between mobile users and traffic management agencies (Mizuta et. al, 2013). Crowdsourcing refers to a 'distributed problem-solving model' soliciting solutions from crowd of undefined size (Chatzimilioudis and Zeinalipour-Yazti, 2013). 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).

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 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".

The contribution of crowdsourcing in improving traffic operational efficiency and logistics in real time is evolving rapidly and qualitatively, creating the need to develop models that characterize smart freight mobility. Therefore, this research develops such analytical models that leverage both crowdsourced data on traffic conditions and data such as commodity flows, fuel consumption etc. of conventional freight to design operations of a smart freight system.

The role of social media and crowdsourcing in transportation applications is rapidly evolving (Misra et. al., 2014, Ali et. al, 2012). The primary sources of transportation-related crowdsourced data - i) social media, ii) mobile applications, and iii) connected vehicles facilitate this evolution which we know as Big Data sources in transportation. Subsequently, crowdsourcing is becoming popular amongst several transportation agencies for real-time road condition assessment and information sharing with road users. 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).

Further, in California, the Traffic Management Teams (TMTs) coordinate closely with Transportation Management Centers (TMCs) for orderly flow of traffic impacted by unusual or unexpected traffic conditions caused by an incident or an event on roadway (Traffic Management Team, 2017). Crowdsourcing as an information sharing platform supplements and supports TMC's real time traffic operations and management needs with wide coverage and low-cost data availability that are easily obtained from the outside transportation community. Although critically beneficial, crowdsourcing has been rarely studied as an influence on freight truck operations vital for the economy. As the congestion on highway continue to grow, dependency on efficient information and communications technology through crowdsourcing could provide smart freight mobility solutions. Challenges particularly exist in reducing fuel consumption, emissions, safety, delays and ton-miles traveled without sacrificing freight performance. Other state transportation agencies such as the Iowa DOT monitors and responds to social media outlets round the clock directly from their Transportation Operations Center (TOC). Utah Citizen Reporting Program allows citizens to report road conditions for Utah DOT, and the District of Columbia DOT has deployed real-time data mining on Twitter feeds for sharing traffic incident information (Adler et. al, 2014).

Motivation

There are existing crowdsourced-based applications such as Waze which provide navigational services by collecting information from app users (Terdiman, D., 2018). However, an app like the Waze cannot be used for performing simulations helpful in determining overall performance of a transportation system. On the other hand, as evident through preliminary literature reviews, several states in the United States have been successfully using crowdsourced data applications for monitoring and enhancing transportation operations – however, not specifically for freight which plays a critical role in sustaining nation's economic competence. Moreover, as there have been several 'smart and connected communities' initiatives from Federal programs that require foundational research and transitioning into scalable and replicable Smart City approaches (Smart and Connected Communities Framework, 2018), contribution of Smart Freight mobility will be the key. One such way would be to allow freight drivers and carriers access to downstream congestion on their path in advance. Thus, allowing flexibility in detouring and rerouting in reaching their destination on time. Application of emerging technologies in the Intelligent Transportation Systems (ITS), such as the connected vehicle technology (CVT) will drive the success of smart freight. However, at present, the knowledge and application of these technologies is scanty or at quite an early stage for the freight industry.

This research demonstrates an important application of emerging technologies (such as crowdsourcing) into freight transportation and logistics. Efficient crowdsourcing-based strategies could be developed that can be improve communication among trucks, avoid congestion points along routes and minimize congestion. This research also demonstrates the level of efficiency that can be achieved in reducing congestion, assist in routing and further

Therefore, this proposed research is a step towards filling this gap in applications of crowdsourcing technology to the development of a smart freight system. The model presented in this paper aims to show some insights on leveraging crowdsourced information on downstream traffic conditions to improve a freight system's performance.

Methodology

The methodology derived in this research can be useful within traffic simulation software packages to enhance both passenger and truck freight operations, and in evaluating impacts of technologies such as CVT which relies on crowdsourced traffic information.

Probabilistic models describing detour maneuvers of trucks subscribed to crowdsourced information of a downstream congestion have been developed. The location of detour maneuvers is chosen close to an exit ramp of a freeway by incorporating the following procedures:

1) Enumerating all possible states represented by vehicle presence around the exit ramp location,
2) Determination of 'Good' states and 'Bad' states.
3) Computing probability of transitioning from state to state (each transition taking an assumed time of 2 seconds), and

4) Computing probability of exiting through the off ramp to use a less congested route.

In this paper, a conceptual framework is developed for enhancing mobility of a system of freight trucks termed as 'smart freight' which have an improved mobility by being able to detour to avoid a downstream congestion on their path. The technique of crowdsourcing is applied to facilitate lane changes and detours using exit ramps for freight trucks. This research involves research methodology will consist of developing stochastic model(s) based on Markov chains. Markov chains have wide applications in freeway traffic congestions. In addition, these encompass defining the stochastic process and the definition follows from Kulkarni (2016). Consider a system at discrete time points n = 0, 1, 2, ... and so on, with X_n being the state of the system at time n. Thus, $\{X_n, n \geq 0\}$ is a discrete-time stochastic process with a countable state-space S as {0, 1, 2, …}. With a fixed value of n as the present time, X_n is the present state of the system. Hence, $\{X_0, X_1, \ldots, X_{n-1}\}$ is the past of the system and $\{X_{n+1}, X_{n+2}, \ldots\}$ is the future of the system. Transition of the system from a state i to another state j occurs with $X_n = i$ and $X_{n+1} = j$ from time n to n+1. Markov property states that given the present state of the system, the future state of the system is independent of the system's past state. This property has several applications for a system with the future only dependent on the present state of the system which contains information needed to probabilistically predict the future. Markov property exhibited by the system defined above is called a discrete-time Markov chain (or DTMC) and is a stochastic process $\{X_n, n \geq 0\}$ with countable state-space S if for all $n \geq 0$, $X_n \in S$ and $i, j \in S$. Thus, for a DTMC $P(X_{n+1} = j \mid X_n = i, X_{n-1}, X_{n-2}, \ldots, X_0) = P(X_{n+1} = j \mid X_n = i)$.

There are several other properties of DTMC which are relevant for applicability in this research. These are discussed as follows:

I. *Time Homogeneous*: A DTMC is said to be time homogenous when it is in a state i at time n and jumps to state j at time n +1 with probability $p_{i,j}$ for all values of n. Thus,

$$P(X_{n+1} = j \mid X_n = i) = p_{i,j}$$

Consider state space $S = \{1, 2, \cdots, m\}$ with *m* being the last finite state of the DTMC, the one-step transition probability matrix (*P*) is:

$$P = \begin{bmatrix} p_{1,1} & \cdots & p_{1,m-1} & p_{1,m} \\ \vdots & \cdots & \vdots & p_{2,m} \\ p_{m-1,1} & \cdots & \ddots & \vdots \\ p_{m,1} & \cdots & p_{m,m-1} & p_{m,m} \end{bmatrix}$$

II. Stochastic Matrix: The transition probability matrix, *P*, for the DTMC defined above has the following stochastic property if:

i. All the elements on each row of the matrix *P* are non-negative, i.e. $p_{i,j} \geq 0$ for all $i, j \in S$, and

ii. The sum of all the elements on each row of the matrix *P* is equal to 1, i.e. $\sum_{j \in S} p_{ij} = 1$ for all $i \in S$.

Based on the above definitions, if initial distribution of X_0 is known, such that $A_0 = P(X_0 = i_0)$, $i_0 \in S$ the finite dimensional joint probability mass function $P(X_0 = i_0, X_1 = i_1, \ldots, X_n = i_n)$ for the DTMC is expressed as:

$$P(X_0 = i_0, X_1 = i_1, \ldots, X_n = i_n) = A_0 p_{i_0,i_1} p_{i_1,i_2} \cdots p_{i_{n-1},i_n}$$

III. Steady State Property: Based on the transition probability $P_{i,j}$, the steady state properties of the DTMC is expressed as:

$\lim_{n \to \infty} (P_{i,j})^n = \pi_j$, with π_j being the steady state probability.

A DTMC $\left\{X_n, n \geq 0\right\}$ with static space *S*, transient probability matrix $P_{i,j}$ that is irreducible is also positive recurrent if and only if there exists a unique solution to $\pi_j = \sum_{i=1}^{n} \pi_i \left(P_{i,j}\right)$.

DTMCs have been used in several real-life situations such as genomics, genetics, genealogy, finance, manpower planning etc. (Kulkarni, 2016)

DTMC Example

Consider a DTMC $\left\{X_n, n \geq 0\right\}$ with state-space $\left\{1,2,3\right\}$ and transition probability matrix $P_{i,j}$ as:

$$P_{i,j} = \begin{bmatrix} 0.1 & 0.6 & 0.3 \\ 0.4 & 0.5 & 0.1 \\ 0.3 & 0 & 0.7 \end{bmatrix}$$

The transition diagram for the above DTMC example is shown in Fig. 1.

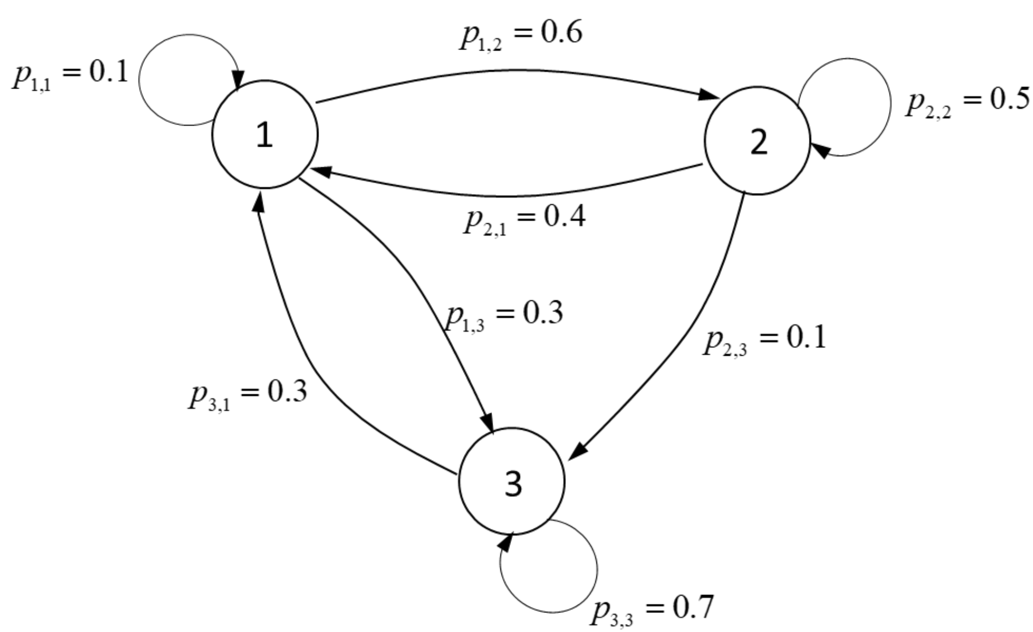


Figure 1: Transition diagram for the example DTMC

Assume that the initial probability distribution of the states is known, and is given by:

$A = [0.1 \;\; 0.2 \;\; 0.7]$

Thus, the joint probability mass function for the DTMC expressed by $P(X_2 = 2, X_1 = 3)$ can be computed as:

$$
\begin{aligned}
P(X_2 = 1, X_1 = 3) &= \sum_{i=1}^{3} P(X_2 = 2, X_1 = 3 \mid X_0 = i).P(X_0 = i) \\
&= \sum_{i=1}^{3} A_i p_{i,3} p_{3,1} \\
&= A_1 p_{1,3} p_{3,1} + A_2 p_{2,3} p_{3,1} + A_3 p_{3,3} p_{3,1} \\
&= 0.1 \times 0.3 \times 0.3 + 0.2 \times 0.1 \times 0.3 + 0.7 \times 0.7 \times 0.3 \\
&= 0.009 + 0.006 + 0.147 \\
&= 0.162
\end{aligned}
$$

The probability mass function of the various states of the DTMC after 10th time interval (i.e. A^{10}) can be computed using the steady state probabilities such that:

$$
A^{(10)} = A.\left(P_{i,j}\right)^{10} = [\,0.1 \;\; 0.2 \;\; 0.7].\begin{bmatrix} 0.1 & 0.6 & 0.3 \\ 0.4 & 0.5 & 0.1 \\ 0.3 & 0 & 0.7 \end{bmatrix}^{10} = [0.2776 \quad 0.3323 \quad 0.3900]
$$

Defining States

This component of research consists of developing states for DTMC. 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. 2 and presents the skeleton of the modeling framework.

Consider the continuous traffic movement (consisting of both passenger cars and freight tucks) along the route segment A-B shown in Fig. 2, with two ramp exits (or route options for freight vehicle) as marked along the segment. There is a downstream congestion along the segment. With no route changes, the usual route to the intermodal facility goes through the congested location; however, with route changes occurring via ramp exit 1 or 2, the freight truck could improve its travel time to its destination and thereby, contribute to reduction in the congestion.

In the sketch of Fig. 2, 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. The crowdsourcing-based information can be subscribed by both the passenger car and freight trucks as illustrated in the sketch of Fig. 2. Thus, 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. Other vehicles that do not have access to the crowdsourced information will continue to proceed towards the congested point.

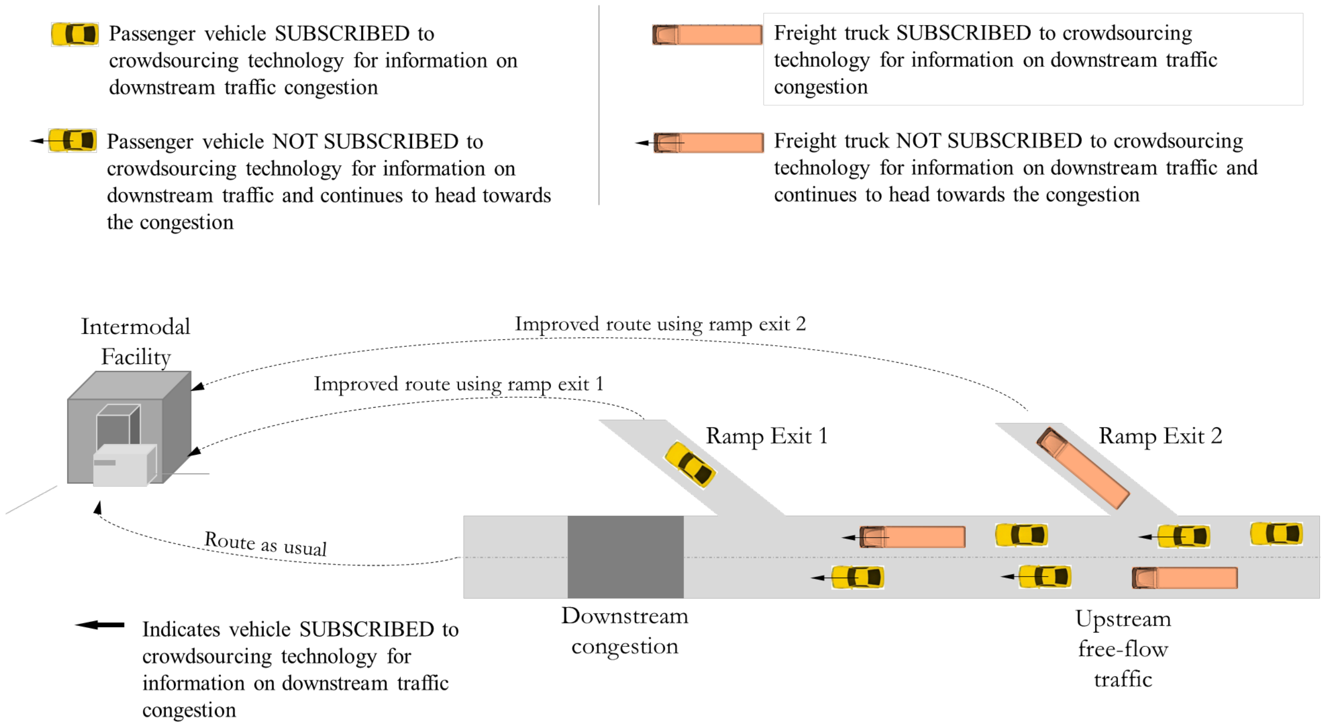


Figure 2: Model set-up for traffic operation on a freeway

The modeling framework shown in Fig. 2 requires input data that are real-time crowdsourced data on traffic situations and freight data related to usual commodity flow, truck tonnage, etc. The model in conjunction with data on fuel consumption per mile and freight tonnage will determine efficiency improvements in operations and mobility of smart freight.

In successfully modeling the application of crowdsourced information to improve freight truck routes, the location of the vehicles on the freeway need to be first determined, especially if the freight truck is upstream, downstream or nearby the ramp exit. The model of detouring developed in this research is represented by on direction of a four-lane freeway close to a ramp exit as shown in Fig. 3. The area around the ramp exit is divided into seven zones for the two lanes. 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.

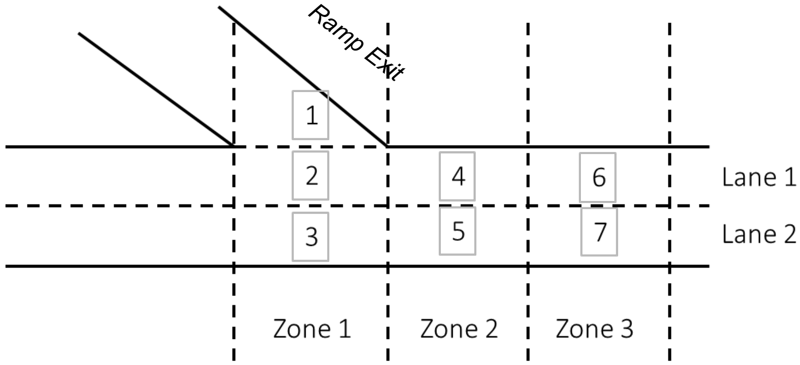


Figure 3: Simplified representation of the area around exit ramps.

The movement of freight trucks across the six zone-lane pairs with one exit ramp case for the seven slots shown in Fig. 3 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 label *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 label *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 label *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 label *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 label *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 label *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 label *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*.

The above probabilities have been shown in Fig. 4, states developed for the DTMC involves the following identification of states represented by vehicle locations around the ramp exit of the highway section.

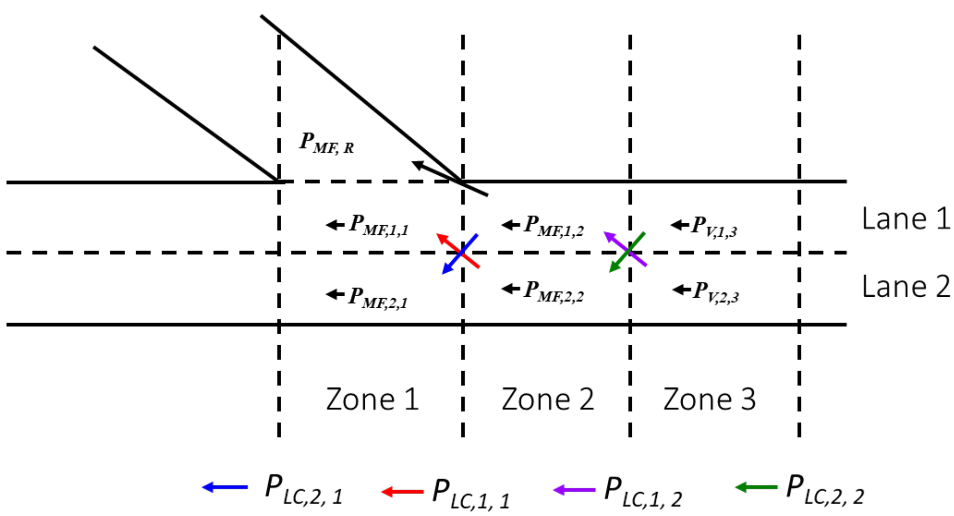


Figure 4: Probabilities of various vehicle movements

States are decided based on the presence of any vehicle and if the vehicle in any of the lane-zone pairs have access to crowdsourced information about an existing downstream congestion. For example, the sketch in Fig. 5 shows the distribution of vehicles across seven lane-zone pairs including one slot on the ramp exit. Presence/absence of a vehicle in a given lane-zone pair is are denoted by the following notations:

0 = Empty *Lane - Zone* pair with no vehicle present.

1 = A vehicle present in the *Lane - Zone* pair and WITHOUT access to crowdsourced information about an existing downstream congestion.

*1** = A vehicle present in the *Lane - Zone* pair and WITH access to crowdsourced information about an existing downstream congestion.

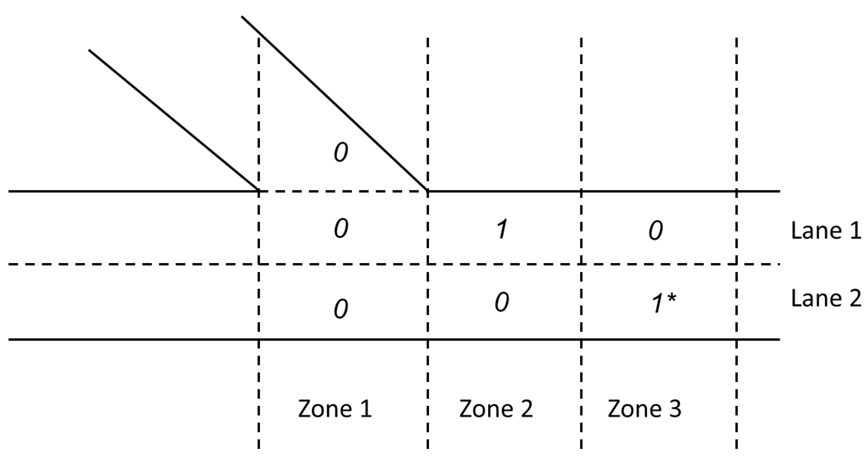
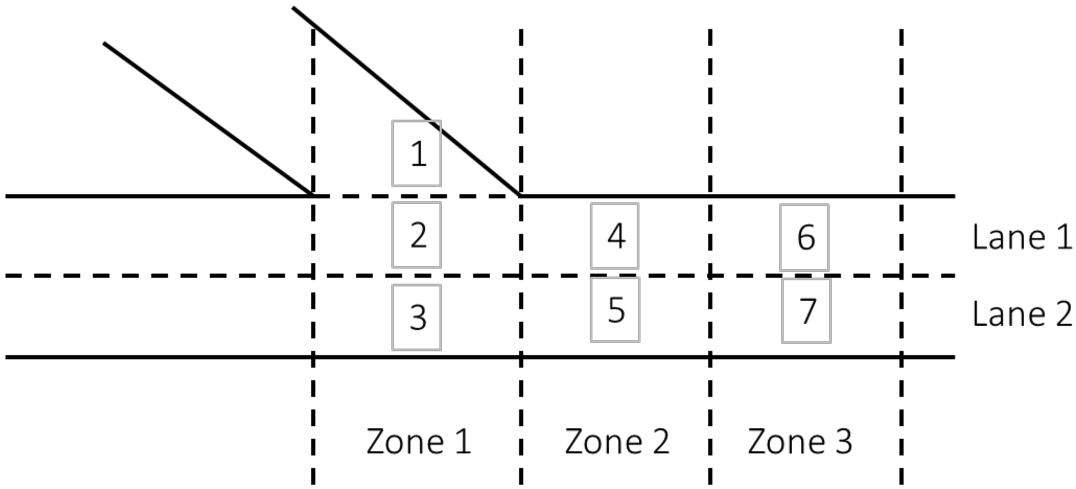


Figure 5: An example state consisting of empty slots (using 0), vehicle 'without access' to crowdsourced information (using 1) and vehicle 'with access' to crowdsourced information (using 1*).

Based on the set-up of seven lane-zone pairs with slots and three vehicle situations present or absent in each of the slots there are a total of 3^7 states (= 2187 states) possible for the DTMC being studied. A sample of these states is presented in Fig. 6 for illustration purpose corresponding to the slot number labels in Fig. 3.



State	**Vehicle Arrangement**						
	Ramp Exit	**Lane 1 –Zone 1**	**Lane 2 –Zone 1**	**Lane 1 –Zone 2**	**Lane 2 –Zone 2**	**Lane 1 –Zone 3**	**Lane 3 –Zone 3**
	Slot 1	**Slot 2**	**Slot 3**	**Slot 4**	**Slot 5**	**Slot 6**	**Slot 7**
1	*0*	*0*	*0*	*0*	*0*	*0*	*0*
2	*0*	*0*	*0*	*0*	*0*	*0*	*1*
3	*0*	*0*	*0*	*0*	*0*	*0*	*1**
4	*0*	*0*	*0*	*0*	*0*	*1*	*0*
…	…	…	…	…	…	…	…
2186	*1*	*1**	*1**	*1**	*1**	*1**	*1**
2187	*1**	*1**	*1**	*1**	*1**	*1**	*1**

Figure 6: Sample of vehicle arrangement for the states across slots

The transition probability matrix is built using the 2187 states identified in Fig. 6. However, not all the probabilities for all the 2187 states would be feasible. See example below in Fig. 7 for the four feasible transitions of state 43 to states 383, 384 and 385 corresponding to the DTMC.

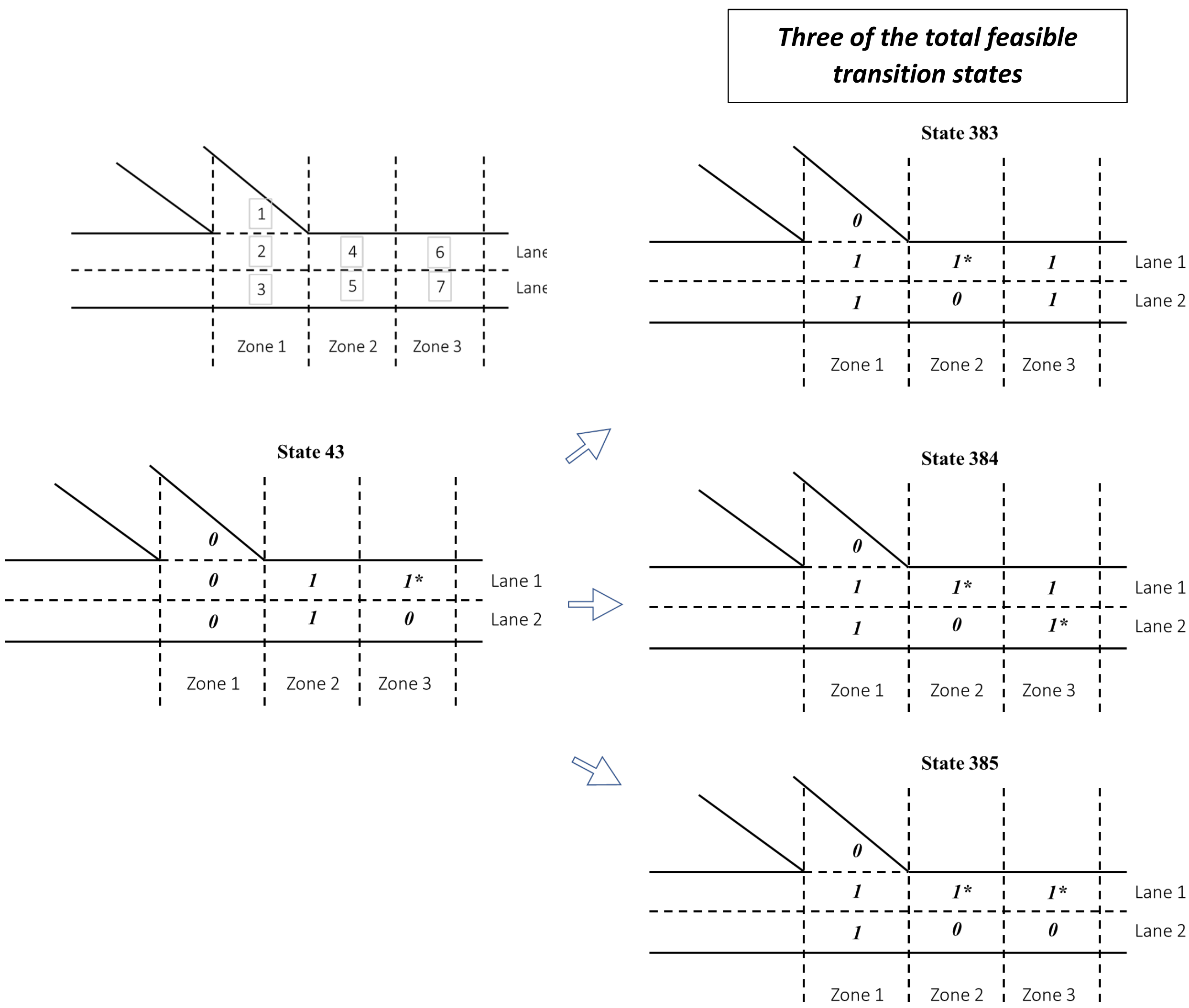


Figure 7: Illustration of few of the possible feasible transition states for state 43 of the DTMC.

In the sketch shown in Fig. 7, there is a vehicle in the slots numbered 4, 5 and 6 of state 43. The freight vehicle in slot 6 is subscribed to crowdsourcing technology and have advance information about the downstream congestion. The other vehicles could be passenger vehicle or freight trucks which are not subscribed to any form of crowdsourcing technology and hence, continue to move forward along their respective lanes. The states 383, 384 and 385 are three of the feasible transition states of state 43 of the DTMC. State 43 transitions to state 383 wherein a passenger vehicle or a freight vehicle enters the last two lane-zone pairs with slots 6 and 7. State 384 has a freight vehicle in slot 7 that has access to crowdsourced information about an existing downstream congestion and one vehicle with no access to crowdsourced information. State 385 has only one vehicle in slot 6 which is a freight truck in slot 6 that has access to crowdsourced information on the downstream congestion.

Similar to the example discussed above all other feasible and infeasible transition states of the DTMC are built as a 2187×2187 sparse matrix. Table 1 presents a section of the sparse matrix of some states. '0' denotes an infeasible transition of a state to another state and 1 denote a feasible transition in the sparse matrix.

Table 1: Sample sparse matrix for some state transitions

After

Before

STATE	**. .**	**379**	**380**	**381**	**382**	**383**	**384**	**385**	**386**	**387**	**388**	**389**	**. .**
:													
38		*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
39		*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*0*	*0*	
40		*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
41		*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
42		*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
43		*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*0*	*0*	
44		*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*1*	
45		*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
46		*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
47		*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
48		*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	
:													

Of all the 2187×2187 possible transitions of one state to next state only 19,863 transitions were found to be feasible. For example, for the given state 43 in Table 1, only nine possible transitions of state exist which are feasible. These states are 379, 380, 381, 382, 383, 384, 385, 386 and 387.

Determination of 'Good' states and 'Bad' States

A '*Good*' state would occur when a freight vehicle which has information of the downstream traffic congestion due to crowdsourcing is *successfully* able to change lane and be able to use the ramp exit. For example, all the freight vehicles subscribed to crowdsourced information of downstream congestion and positioned as shown in the states 3, 12, 389 and 1015 shown in Fig. 8, are able to eventually use the ramp exit. Since a state transition occurs with each new time interval, the freight truck in Lane 2 – Zone 3 of state 3 will reach the ramp exit in the next two time intervals. Similarly, the freight trucks in states 12 and 1015 will reach the ram exit in the second time interval. The freight truck for state 389 will reach the ramp exit in the very next time interval. There were a total of 312 good states which were identified for the DTMC.

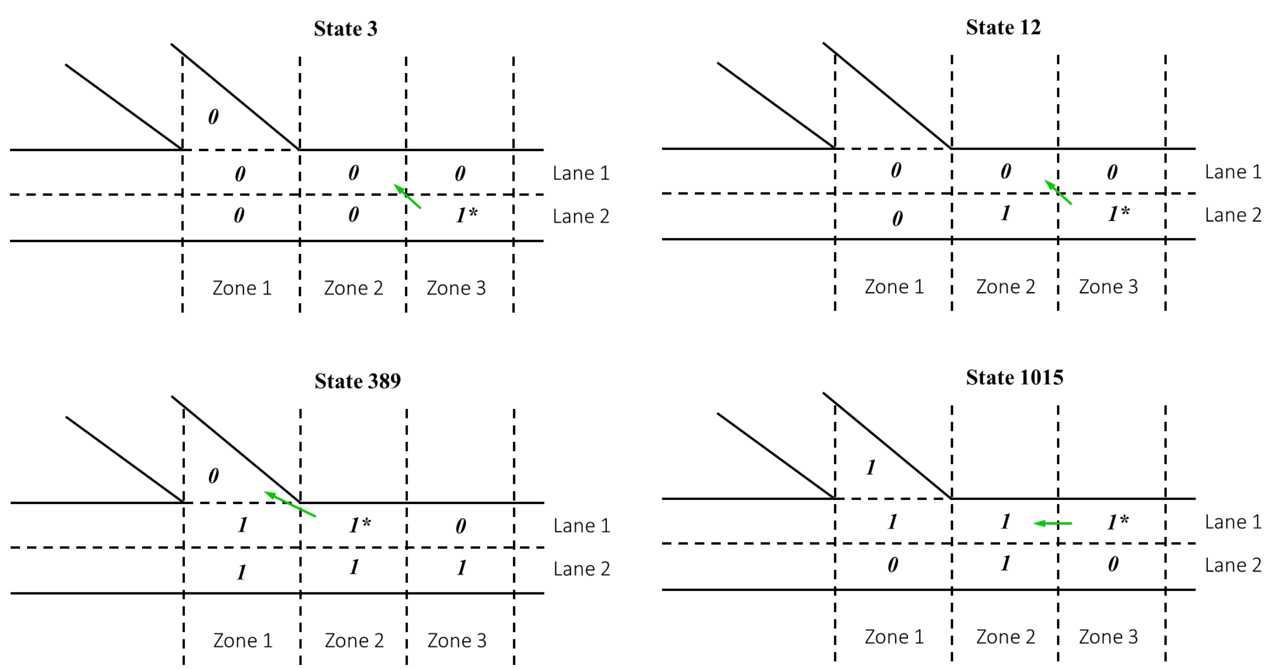


Figure 8: Examples of 'good' states of DTMC

A '*Bad*' state results when a freight vehicle, although having information about downstream congestion through crowdsourcing, is *unable* to do a lane change to reach the ramp exit, and hence, is constrained to continue to move forward along the highway. For example, the states 6, 133, 1530 and 2080 shown in Fig. 9 illustrate that a freight truck although having access to crowdsourced information on downstream congestion will not be able to do a lane change in the next state. The lane change is thwarted because there is a vehicle present in Lane 1- Zone 3 of state 6, Lane 1- Zone 2 of state 133 and Lane 1- Zone 3 of state 1530 which will move forward to occupy the slot in front. For state 2080, the freight vehicle cannot move to the ramp exit although being subscribed to the downstream traffic congestion. There is a total of 720 states which were identified as bad states for the DTMC.

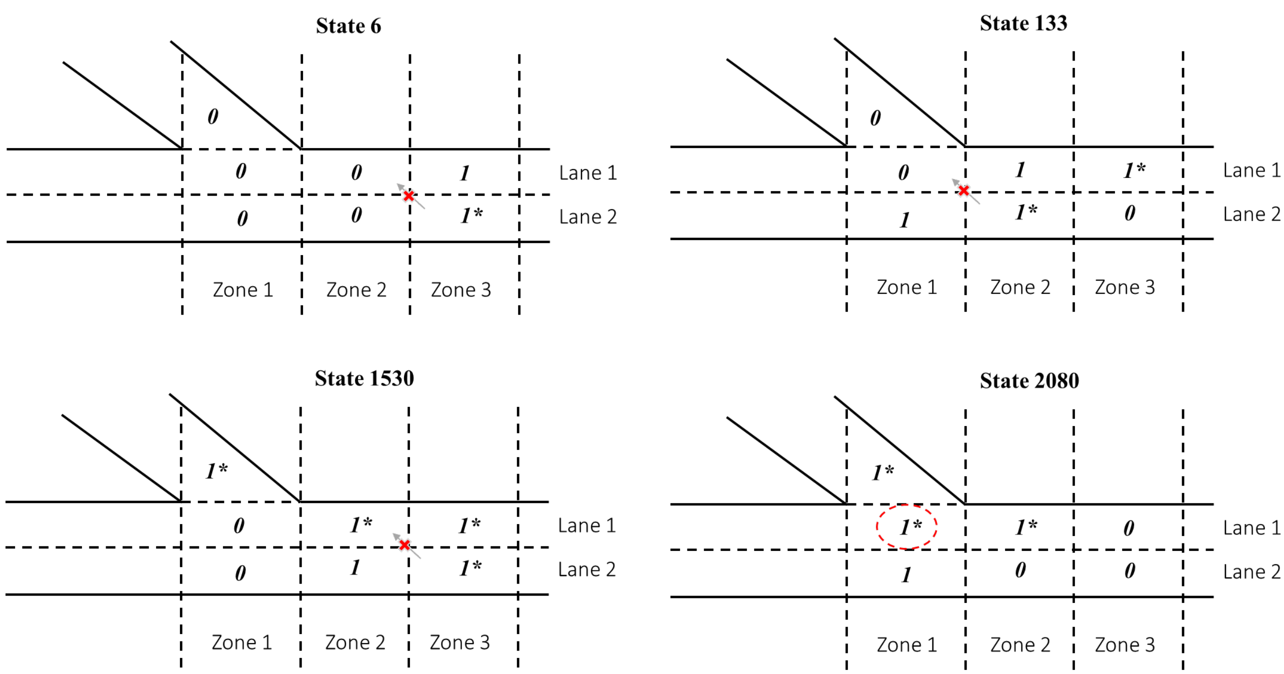


Figure 9: Examples of ‘bad’ states of DTMC

Transition Probabilities

Probabilities for transitioning from one state to another state is computed by taking into consideration the following probabilities:

i. Arrival or non-arrival of a vehicle in slot 6 (Lane 1- Zone3), i.e. $P_{V,1,3}$

ii. Arrival or non-arrival of a vehicle in slot 7 (Lane 2- Zone3), i.e. $P_{V,2,3}$

iii. Moving forward of a vehicle from one slot to another slot, i.e. $P_{MF,1,1}$, $P_{MF,1,2}$, $P_{MF,2,1}$, $P_{MF,2,2}$ and $P_{MF,R}$.

iv. Lane change of a vehicle to another vehicle, $P_{LC,1,\ 1}$, $P_{LC,2,\ 1}$, $P_{LC,1,\ 2}$, and $P_{LC,2,\ 2}$.

Thus, the product of the above 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:

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

Application Example

An example application of the DTMC model developed in this research is carried out using simulation exercise. Data from the transportation network of the Freight Analysis Framework (FAF) (FAF Data, 2017) as well as truck route network (Caltrans GIS Data, 2017) are used in a Geographical Information System (GIS) format from the Southern California Region. TAZ centroids (as origins) close to San Diego Fwy (I-405 N) and LA Intermodal Facility in Southern California (as destination) has been used in the simulation. The simulation is carried out with the ramp Exit 24 on I-405 N, merging towards the I-605 N. A congestion zone is artificially created downstream this exit point on I-405 N. Data for annual average daily traffic (AADT), both passenger and truck, have been obtained from highway data available on the Caltrans website. The set-up used for carrying out the simulation is shown in Fig. 10. The length of each zone is 175-ft which is equivalent to 2-second headway for speed limit of 60 mph on the freeway, see Fig. 11.

Figure 10: Ramp exit used for simulation [Image Source: Google Street View]

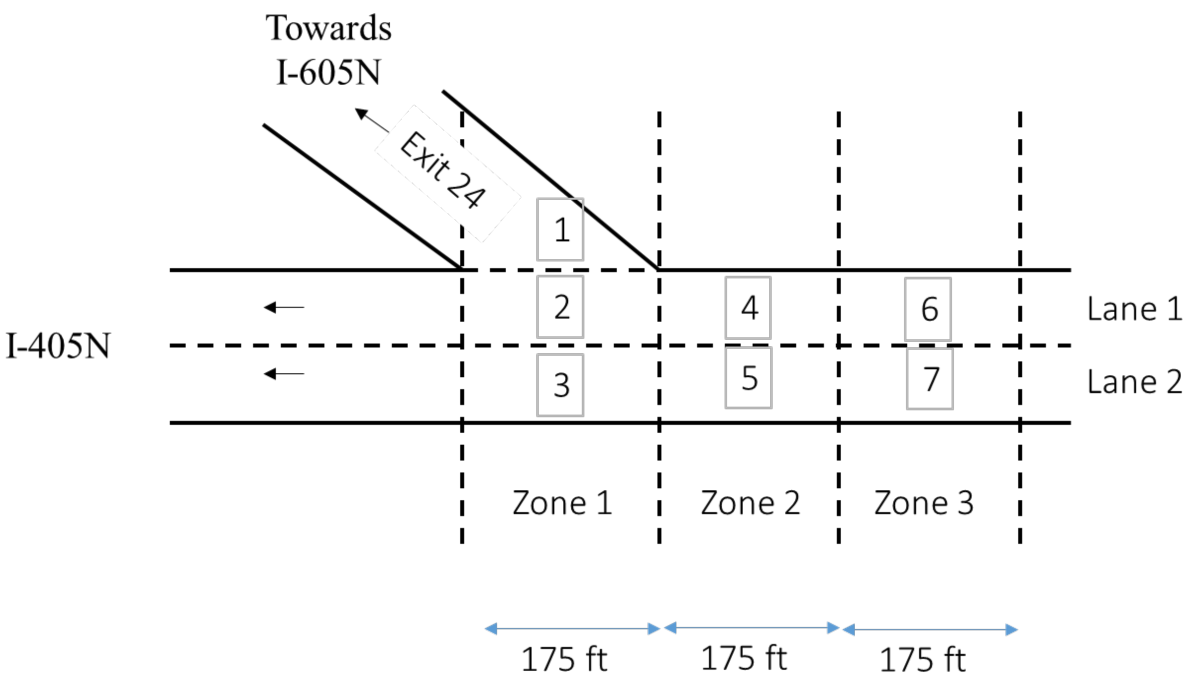


Figure 11: Simplified set-up for simulation exercise

Performance Evaluation with Crowdsourcing

The performance measure underlying the utility of crowdsourcing was assessed using the number of vehicles that were able to avoid downstream congestion with information available of the traffic situation in advance. This was carried out using the 'good' and 'bad' states of the DTMC. The transition matrix, P, developed in the process was divided into Good states and Bad states and partitioned as follows:

$$P = \begin{bmatrix} p_{GG} & p_{GB} \\ p_{BG} & p_{BB} \end{bmatrix} \tag{2}$$

where, p_{GG} is the probability of going from a good state to a good state, p_{GB} is the probability of going from a good state to a bad state, p_{BG} is the probability of going from a bad state to a good state and p_{BB} is the probability of going from a bad state to a bad state. The transition matrix P defines expressions for conditional probabilities denoting failure of a vehicle to be able to use the ramp exit. Table 2 provides input values used for various individual probabilities.

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 $P_{LC,2,2}$	0.3 (denotes lane change is not allowed) and 0.8 (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 $P_{LC,1,2} = (1 - P_{LC,2,2})$

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 analyzed 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.

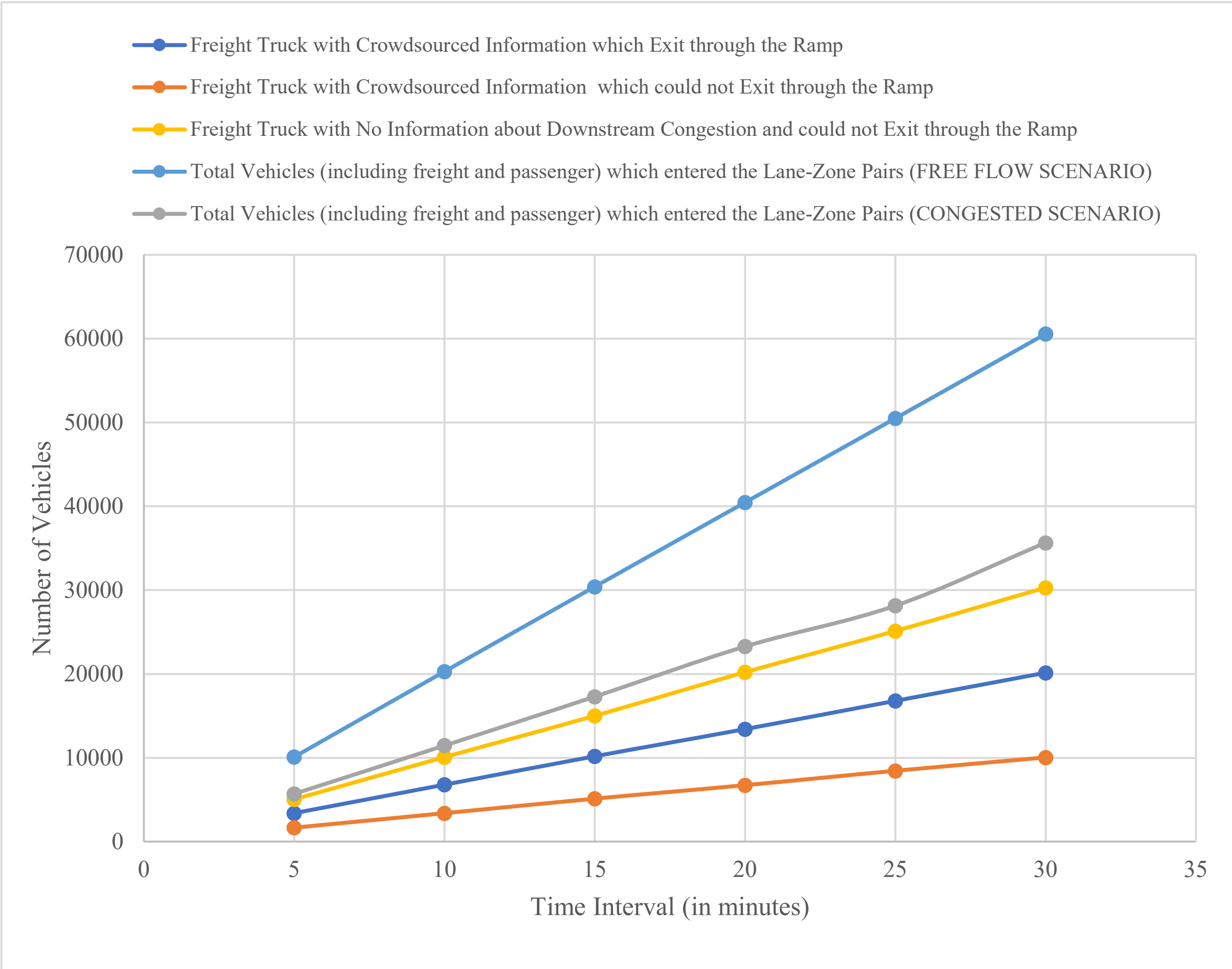


Figure 12: Simulation results indicating improvement in freight truck routing with crowdsourced information

Concluding Remarks

There are existing crowdsourced-based applications such as Waze which provide navigational services by collecting information from app users. However, there are limited use of an app like the Waze limit its usage in simulations required to determine performance of freight operations. Preliminary literature reviews, several states in the United States have been successfully using crowdsourced data applications for monitoring and enhancing transportation operations – however, not specifically for freight which plays a critical role in sustaining nation's economic competence. This research involves research methodology will consist of developing stochastic model(s) based on Markov chains to improve freight as well as passenger operations. 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 is 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 modeling framework requires input data that are real-time crowdsourced data on traffic situations and freight data related to commodity flow, truck tonnage, etc. Results indicate that of the total vehicles (auto and truck) subscribed to crowdsourcing, freight trucks represent approximately 33%. Trucks subscribed to crowdsourcing information can successfully use off-ramps to avoid downstream congestion. The model output developed in this research can also provide estimated savings in fuel consumption per mile and increased movement of freight tonnage to quantify the benefits of smart technology.

Future research involves performing delay analysis with the travel time increase from the freight vehicles that add to the downstream congestion. With an example of freight routes, it is expected that a truck would avoid a congested point on a route by utilizing crowdsourced information. Thus, the volume on the given link of congestion should decrease minimizing that link's travel time based on the standard Bureau of Public Roads (BPR)-type function (Lu et. al, 2016):

$$t_a = t_a^0 \left[1 + 0.15 \left(Q / y \right)^4 \right] \tag{3}$$

where, t_a denotes the average travel time of the study road segment a, t_a^0 denotes the free-flow travel time, and Q, y are the aggregated traffic flow and road capacity in passenger car units. Thus, with decrease in Q or the freight truck flow, there will be observed increase in route mobility and resilience due to lowering in travel times.

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References

Adler, J., Horner, J., Dyer, J., Toppen, A., Burgess, L. and Hatcher, G., 2014. Estimate benefits of crowdsourced data from social media (No. FHWA-JPO-14-165). United States. Dept. of Transportation. ITS Joint Program Office.

Ali, K., Al-Yaseen, D., Ejaz, A., Javed, T. and Hassanein, H.S., 2012, April. Crowdits: Crowdsourcing in intelligent transportation systems. In Wireless Communications and Networking Conference (WCNC), 2012 IEEE (pp. 3307-3311). IEEE.

Alvaro, N., Conway, M., Doan, S., Lofi, C., Overington, J. and Collier, N., 2015. Crowdsourcing Twitter annotations to identify first-hand experiences of prescription drug use. Journal of biomedical informatics, 58, pp.280-287.

Brabham, D.C., 2008. Crowdsourcing as a model for problem solving: An introduction and cases. Convergence, 14(1), pp.75-90.

Brabham, D.C., 2009. Crowdsourcing the public participation process for planning projects. Planning Theory, 8(3), pp.242-262.

Caltrans GIS Data, accessed on March 31, 2017. http://www.dot.ca.gov/hq/tsip/gis/datalibrary/#Highway

Caltrans Partners with Waze Connected Citizens Program, Caltrans Press Release, accessed on March 31, 2017. http://www.dot.ca.gov/paffairs/pr/2016/prs/16pr033.html

Caltrans' QuickMap, accessed on March 31, 2017. http://quickmap.dot.ca.gov/

Chatzimilioudis, G. and Zeinalipour-Yazti, D., 2013, June. Crowdsourcing for mobile data management. In Mobile Data Management (MDM), 2013 IEEE 14th International Conference on (Vol. 2, pp. 3-4). IEEE.

Evans, J.L., Elefteriadou, L. and Gautam, N., 2001. Probability of breakdown at freeway merges using Markov chains. Transportation Research Part B: Methodological, 35(3), pp.237-254.

Ferster, C., Nelson, T., Laberee, K., Vanlaar, W. and Winters, M., 2017. Promoting crowdsourcing for urban research: Cycling safety citizen science in four cities. Urban Science, 1(2), p.21.

Freight Analysis Framework Data, accessed on March 31, 2017. http://www.ops.fhwa.dot.gov/freight/freight_analysis/faf/index.htm

Gao, H., Barbier, G., Goolsby, R. and Zeng, D., 2011. Harnessing the crowdsourcing power of social media for disaster relief. Arizona State Univ Tempe.

Howe, J., 2006. The rise of crowdsourcing. Wired magazine, 14(6), 1-4.

Juhlin, O. Social media on the road. Kista, Sweden: Springer, 2010.

Kulkarni, V. G., 2016. Modeling and analysis of stochastic systems. Chapman and Hall/CRC.

Langer, T. and Vaidyanathan, S., 2014, July. Smart Freight: Applications of Information and Communications Technologies to Freight System Efficiency. American Council for an Energy-Efficient Economy.

Magtoto, J. and Roque, A., 2012, November. Real-time traffic data collection and dissemination from an Android Smartphone using proportional

Lu, Z., Meng, Q., and Gomes, G., 2016. Estimating link travel time functions for heterogeneous traffic flows on freeways. Journal of Advanced Transportation, 50(8), 1683-1698.

computation and freesim as a practical transportation system in Metro Manila. In TENCON 2012-2012 IEEE Region 10 Conference (pp. 1-5). IEEE.

Misra, A., Gooze, A., Watkins, K., Asad, M. and Le Dantec, C., 2014. Crowdsourcing and its application to transportation data collection and management. Transportation Research Record: Journal of the Transportation Research Board, (2414), pp.1-8.

Mizuta, A., Swindler, K., Jacobson, L. and Kuciemba, S., 2013. Impacts of Technology Advancements on Transportation Management Center Operations (No. FHWA-HOP-13-008).

Nurdden, A., Rahmat, R.A.O.K. and Ismail, A., 2007. Effect of transportation policies on modal shift from private car to public transport in Malaysia. Journal of applied Sciences, 7(7), pp.1013-1018.

Östergren, M. and Juhlin, O., 2005. Road Talk: a Roadside Location-Dependent Audio Message System for Car Drivers. J. Mobile Multimedia, 1(1), pp.47-61.

Smart Roadside, Intelligent Transportation Systems, Joint Program Office, accessed on March 31, 2017. https://www.its.dot.gov/factsheets/smart_roadside.htm

Smart and Connected Communities Framework, Networking and Information Technology Research and Development, accessed on October 23, 2018. https://www.nitrd.gov/sccc/

Sun, Y., Moshfeghi, Y. and Liu, Z., 2017. Exploiting crowdsourced geographic information and GIS for assessment of air pollution exposure during active travel. Journal of Transport & Health, 6, pp.93-104.Traffic Management Team, California Department of Transportation. Accessed on March 31, 2017. http://www.dot.ca.gov/trafficops/tm/docs/Policy_Memo_TMT_1994.pdf

Terdiman, D. (August 6, 2009). "CNET News – Waze iPhone app provides real-time, crowdsourced traffic data". CNET. Accessed on December 9, 2018. https://www.cnet.com/news/waze-iphone-app-provides-real-time-crowdsourced-traffic-data/

Wang, X., Zheng, X., Zhang, Q., Wang, T. and Shen, D., 2016. Crowdsourcing in ITS: The state of the work and the networking. IEEE transactions on intelligent transportation systems, 17(6), pp.1596-1605.

Zheng, X., Chen, W., Wang, P., Shen, D., Chen, S., Wang, X., Zhang, Q. and Yang, L., 2016. Big data for social transportation. IEEE Transactions on Intelligent Transportation Systems, 17(3), pp.620-630.