# VANET-based Smart Navigation for Vehicle Crowds: FIFA World Cup 2022 Case Study

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***Abstract*—Non-recurrent events (e.g. football events or evacuation in case of natural disasters) pose great challenges to vehicle routing and traffic management in Intelligent Transportation Systems (ITSs). The high traffic demand during such events, combined with the road network resource constraints, bring forward the need for efficient and smart management techniques that better utilize the network facilities while maintaining a certain performance level. Vehicular Ad-hoc Networks (VANETs) and the advancement in information technology bring new opportunities to address such problems. This paper utilizes VANETs to build a vehicular crowd management system that utilizes system-optimum stochastic routing. The objective is to clear the network in a shorter time by better utilizing the available network resources. To build this system, vehicles are used as sensors that communicate the network state information to the Traffic Management Center (TMC) in real time. A linear programming model is developed to minimize the network-wide travel time constrained by the road link capacities based on the collected information. The results show that the proposed system decreases the network-wide travel time and is successful in clearing the network earlier by up to $38\%$ compared to deterministic user-equilibrium traffic assignment.**

***Index Terms*—VANET-based Navigation, Stochastic Routing, Constrained Routing.**

## I. Introduction

Merging advanced Information and Communication Technology (ICT) into Intelligent Transportation Systems (ITSs) has shown significant improvements in both vehicle mobility and safety by reducing travel time [1], fuel/energy consumption [2], [3], crash probability, and accidents severity [4].

As ICT becomes an integral part of ITS, significant research efforts are being allotted to utilize such technologies in more advanced ways. Vehicular navigation systems based on real time information is an important research direction showing potential benefits which include reducing travel time [5], [6], and energy/fuel saving [7].

Despite the ability of such navigation techniques to efficiently route vehicles and save travel time and energy, most of them fail when there are heavy vehicular crowds in the case of special large events such as large public gatherings at a sporting event or emergency evacuation, in case of natural disasters. One reason for this limitation is that, as these events are non-recurrent, the road networks are not designed to support this high traffic volume during such events, where higher road capacities [8] and special traffic control [9] are needed. The second reason is that many of these techniques are based on the minimum path algorithms, and thus produce the user-optimum traffic assignment solution. The best path routing techniques do not account for other parameters such as road capacities, traffic volume, or underutilized alternative routes. Moreover, at any given time, shortest path navigation techniques provide the same guidance for all vehicles on the road based on the destination, causing the shortest path to collapse, while other longer paths are empty. It also results in route oscillations and unstable global traffic behavior [10].

The high traffic demand during large events or in evacuation scenarios, combined with the road network resource constraints (including the road link capacities, traffic signals, turn/link/lane prohibitions), raise the need for efficient and smart route planing techniques. Such techniques would better utilize the network facilities, while maintaining a certain performance level that satisfies the driver's expectations.

Because of the importance of the crowd management [11], this paper focuses on utilizing the advancements in vehicular communication [12], to efficiently route vehicular crowds to minimize the network-wide travel time and to clear the network faster. The proposed system uses vehicles as network sensors and utilizes VANETs as an infrastructure to collect road state-conditions (traffic volume and travel time on each road segment) in real-time. The collected information is used along with historical information to optimize the network-wide vehicular traffic-assignment using linear programming [13]. In the optimization problem, the road capacity and its current traffic load are used to constrain the network congestion. The main idea behind the proposed model is to efficiently utilize all the network resources, allowing vehicles traveling from the same origin to the same destination, at the same time to be assigned different routes. Consequently, in order to minimize congestion and improve the network-wide mobility, some vehicles may be subjected to longer travel times.

To test our proposed model, we use the FIFA World Cup 2022, which will be held in Qatar, as a case study. The Doha road network in Qatar, is implemented and used to compare our proposed system to the dynamic time-dependant incremental user-optimum traffic assignment which is typical real-time navigation systems that are currently in use.

The remainder of the paper is organized as follows. Section II explores the related work. Section IV describes the proposed

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system and its components. Section V describes our case study on Doha network in Qatar and the results. The final conclusions are presented in VI.

## II. Previous Works

Online services, such as Google Maps and Waze, provide online dynamic navigation guidance based on the estimated travel time information collected from vehicles or mobile devices. Other online services, such as INRIX [14], provide real-time traffic information to assist driver and autonomous vehicles selecting routes. Some research efforts [5], [6] propose a mobile crowd sensing that use both current and historical information to predict the traffic condition and traveling speed. The objective is to enable dynamic routing of drivers wishing to avoid congestion. All these guidance systems utilize the shortest path techniques (which are user equilibrium models) or at most provide alternative routes without considering the system-wide performance or trying to minimize network-wide congestion.

Some researches consider balancing the traffic across alternative routes. For instance, the authors of [10] propose a heuristic approach "Entropy Balanced k Shortest Paths" to assign vehicles to different routes randomly based on the vehicle's remaining travel time and the route popularity. Compared to this algorithm, our proposed model is a step up because we utilize optimization to assign routes instead of assigning routes randomly. Moreover, our proposed model accounts for the current network-wide states in assigning the traffic (i.e. the current traffic load on each road segment).

The authors in [15] present an evacuation route planning model by computing the relationship between the clearance time, number of evacuation paths, and congestion probability during an evacuation. The model in [15] does not utilize vehicular networks and does not account for the current network conditions. Instead, it focuses on road capacity uncertainty. In our work, we collect the road information, based on which, we can estimate the available road capacities. Consequently, a portion of the traffic can be assigned to these underutilized routes. In [16], the authors developed a system-optimum eco-routing model to minimize the fuel consumption. By utilizing multiple routes they were able to reduce the traffic congestion, consequently, reduce the fuel consumption. Compared to [16], our proposed model focuses on the objective of clearing the network faster by enabling vehicles to use alternative routes at the same time.

## III. Network Model and Problem Definition

Fig. 1 shows the network model being studied in this paper. The road network is represented by a directed graph $\mathcal{G}(\mathcal{N}, \mathcal{L}, \mathcal{C})$, where $\mathcal{N} = \{i : i = 1, 2, ..., n\}$ is a set of $n$ nodes and $\mathcal{L}$ is a set of $l$ directed links (road segment), i.e., $\mathcal{L} = \{L_{i,j} : i, j \in \mathcal{N}\}$, where $L_{i,j}$ is the road segment from node $i$ to node $j$. Each road segment has a capacity $C_{i,j}$ which is the maximum traffic flow rate that can exit this link. And each segment has a variable travel time $T_{i,j}$ that depends on the traffic conditions on each segment.

In the network, we assume that there is a vehicular crowd, represented by the red area in Fig. 1. In our case study, this red area represents a stadium where some matches will be held. The destinations of these vehicles are distributed across the network. Consequently, these vehicles are grouped into a set of Origin-Destination (OD) demand pairs based on their destinations. Each OD pair is a traffic flow from the stadium to a destination, as shown by the yellow arrows in Fig. 1.

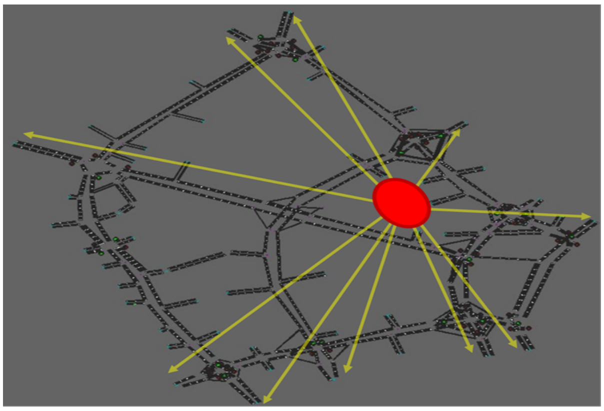


Fig. 1: The Network Model

Thus, we assume that there is a set $\mathcal{F}$ of $f$ concurrent flows, each flow is identified by $k \in \{1, 2, ..., f\}$, and each has $V_k$ cars that need to leave within a time interval $\tau$. Therefore, each flow $k \in \mathcal{F}$ has a traffic rate $q^k$ (in vehicles per hour $veh/h$), where $q^k = V_k/\tau$. We assume these vehicles are connected and follow the route recommendations they receive from the Traffic Management Center (TMC). So, we call these flows the controlled traffic (CT).

In addition to CT, we assume that there is a background traffic (BT) that is traversing the network. Vehicles in the BT use the dynamic time-dependent best path routing.

Our objective is to assign routes to the CT vehicles in such a way that minimizes the network-wide travel time, consequently, clear the network faster.

## IV. Vehicular Crowd Management Framework

This section describes the proposed framework and its components, including the data collection and processing, the optimization problem formulation and its constraints, and the stochastic route construction algorithm.

In contrast to deterministic shortest path routing, the proposed system applies stochastic system-optimum routing. The main goal is to utilize all the available network resources by routing vehicles (going to the same destination) simultaneously through alternative routes while maintaining traffic load on each road segment within its capacity. To achieve these objectives, the system uses vehicles as sensors to collect network-state information in real-time. The collected data is processed and fused with historical data, and then used to optimize the traffic-assignment. By traffic-assignment we simply mean the portion of each flow $k$ that will be assigned to each road segment (described in detail in subsection IV-B).

After computing the optimized traffic-assignment, the TMC constructs stochastic routes for vehicles upon receiving routing requests. Fig. 2 shows the three components of the system.

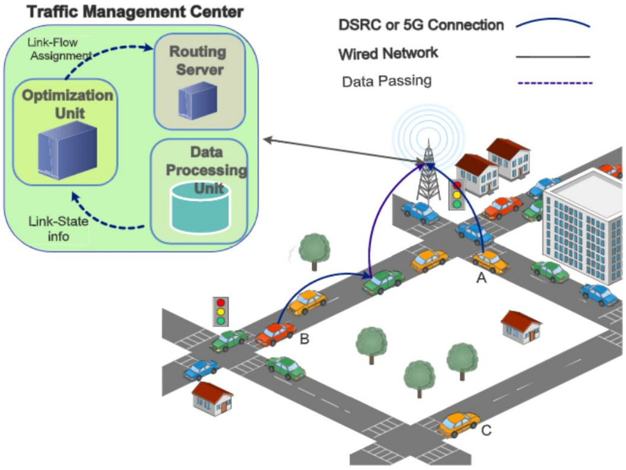



Fig. 2: System Components

### A. Data Collection and Processing

Vehicular network is an integral part in our system. We assume that there is a set of Road Side Units (RSUs) installed in the network through which vehicles can communicate to the TMC. Because the RSU deployment cost, they can not cover the whole network. Thus vehicles can communicate to the TMC using either vehicle-to-infrastructure (V2I) or Vehicle-to-Vehicle (V2V) multi-hop connections. The RSUs are connected to TMC as shown in Fig. 2. In addition to vehicle connectivity, we assume that each vehicle is equipped with a Global Positioning System (GPS), so a vehicle can identify which link it is traversing. These facilities are used to communicate the information needed by the TMC to compute two parameters for each road link $L_{i,j}$: the travel time $T_{i,j}$ and the current traffic load $\zeta_{i,j}$.

Whenever, a vehicle enters a new road segment, it initializes the travel time to the current time, and when it exits this road segment, it computes its travel time on this segment. Subsequently, it builds a message with this information along with the current time as well as the next link to be traversed. The message format is shown in Fig. 3. The vehicle then tries to send this message to the TMC using either V2I (such as car A in Fig. 2) or V2V (such as car B in Fig. 2). If the car does not have a connection (car C in Fig. 2), it will store the message until reaching an area covered by the network, or finding a vehicle-to-vehicle path to the TMC.

When the TMC receives a message, it finds whether it is expired by comparing the current time to the message time stamp. The message expiry interval is assumed to be 180 seconds. The unexpired messages are used to update the link travel times. The TMC fuses the new travel with the historical data using exponential smoothing (in our case we used an exponential factor $\alpha = 0.2$), as shown in Eq. 1.

| 0 | 8 | 16 | 24 | 32 | 40 | 48 | 56 |
|---|---|---|---|---|---|---|---|
| Code | | | | | | | |
| Seq_Num | | | | VehicleID | | | |
| LinkID | | | | Link Travel Time | | | |
| Currnt Time | | | | Next LinkID | | | |

Fig. 3: The Link-State Message Format

$$T_{i,j}^{t} = \alpha\ T_{i,j}^{t-1} + (1-\alpha)\ \widehat{T}_{i,j} \quad (1)$$

where $T_{i,j}^{t}$, $T_{i,j}^{t-1}$ , and $\widehat{T}_{i,j}$ are the new travel time of link $L_{i,j}$ , the old value, and the received update, respectively.

To compute the currant traffic load on each road link, the system uses the "$Next\ LinkID$" field in the received messages. It maintains a linked-list for each road segment that stores the times at which vehicles enter this link in the last 180 seconds (which is the same as the expiry time). Periodically, the system computes the average inter-arrival interval and the traffic volume on each segment. Then, it fuses this new rate with the link history in the same manner as the travel time. The importance of maintaining a linked-list for each segment is to enable the system to consider the delayed packets within the last 180 seconds interval.

The link-state information is then used by the traffic assignment optimization

### B. Traffic Assignment Optimization

The optimization problem is formulated to allow vehicles from same traffic flow $k$ to use different paths at the same time. Consequently, allows load-balancing the traffic among different alternative routes.

*An Illustrative Example*

To understand how to optimize the traffic assignment, we give this illustrative example in Fig. 4, where there is a stretch of highway (HW) and an alternative arterial road (AR) which has longer travel time. The HW has a reduction of lanes (at point A) from 3 lanes to 2 lanes. If the steady state traffic rate entering the HW is low, all the cars will take the HW since its capacity is sufficient. However, if the steady state traffic rate increases, congestion will take place at point A and will spill back creating a queue on the HW, while leaving the AR underutilized. Using the shortest path routing, this congestion will continue, and will lead to increasing the travel time of the HW until it becomes longer than that of the AR. At this point, cars will start switching to the AR causing congestion on it (because of the high traffic rate). So, the congestion will switch between the HW and the AR.

In contrast, our model will divide the traffic flow between the HW and the AR. For instance, if the traffic flow rate is $\mu\ veh/h$, then $\beta.\mu\ veh/h$ will take the HW and $\gamma.\mu\ veh/h$ will take the AR, where $\beta$ and $\gamma \in [0, 1]$, and, in this example, $\beta+\gamma = 1$. Here, $\beta$ and $\gamma$ are called the link-flow assignment. These link-flow assignment parameters must be computed in such a way that minimizes the network-wide travel time, while maintaining the total flow on each road within the road capacity.

*The Optimization Problem*

The linear program should be formulated in such a way that minimizes the network-wide travel time by computing

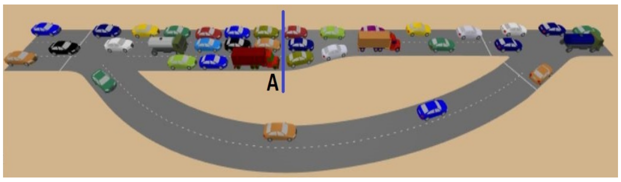



Fig. 4: Example Scenario

the link-flow assignment parameters for each link-flow pair. Vehicles in the $k^{th}$ flow whose rate is $q^k$ can be assigned different links. The link-flow assignment denoted by $q^k_{i,j}$ (corresponding to $\beta$ or $\gamma$ in the illustrative example), is the portion of this traffic flow $k$ that will go through $L_{i,j}$. Based on this definition, the optimization problem can be formulated as:

$$
\begin{aligned}
&\underset{q^k_{i,j}}{\text{minimize}} \sum_{i=1}^{n}\sum_{j=1}^{n} T_{i,j} \sum_{k=1}^{f} q^k_{i,j} \\
&\text{subject to :} \\
&\sum_{d=1}^{n} q^k_{i,d} - \sum_{s=1}^{n} q^k_{s,i} = 0, \qquad \text{if } i \text{ is an intermediate node} \\
&\sum_{d=1}^{n} q^k_{i,d} - q^k = 0, \qquad \text{if } i \text{ is the source of the } k^{th} \text{ flow} \\
&q^k - \sum_{d=1}^{n} q^k_{s,i} = 0, \qquad \text{if } i \text{ is the destination of the } k^{th} \text{ flow} \\
&\zeta_{i,j} + \sum_{k=1}^{f} q^k_{i,j} \leqslant C_{i,j} \quad \forall \ L_{i,j} \in \mathcal{L}, \\
&q^k_{i,j} \geq 0.
\end{aligned}
\tag{2}
$$

where $i, s, d \in \mathcal{N}$ such that $L_{i,d}$ is a link exiting node $i$, and $L_{s,i}$ is a links entering node $i$.

The objective function of the LP problem shows that, if the network has $f$ flows and $l$ links, the linear program calculates $f$ portions for each of the $l$ links. Consequently, the total number of variables in the program will be $l.f$.

In our problem there are three sets of constraints. The first is to satisfy the route continuity. The second is to guarantee that total flow rate on each link does not exceed its capacity, and finally the positive traffic assignment.

**The Route Continuity Constraints:** This set of constraints is represented by the first three constraints in the LP in Eq. 2. The objective of this constraint is to ensure that the computed traffic-flow assignment results in a connected route for each flow $k$ to its destination. The route continuity condition is achieved by enforcing the individual flow balance at each node, which can be formulated as follows.

- For each intermediate node $i$, and for each individual flow $k$, the summation of the sub-flows of the $k^{th}$ flow entering this $i^{th}$ node must be equal to the summation of the sub-flows of the $k^{th}$ flow exiting this node.
- For each source or destination node, we add or subtract the total flow rate $q^k$. For instance, for the source node $i$ that generates the $k^{th}$ flow whose rate is $q^k$, we assume there is another fictitious source sending $q^k$ to it, then node $i$ sends these vehicles to other nodes $d \in \mathcal{N}$. And vice verse for the destination nodes.

This set of constraints has $n \times f$ constraints.

**The Link Capacity Constraints:** For each directed link $L_{i,j} \in \mathcal{L}$, the total flow rate traversing it should not exceed its capacity $C_{i,j}$. The total traffic rate on the link is calculated as the summation of its current load $\zeta_{i,j}$ (computed based on the received link-state information messages) and all the flows/sub-flows assigned to this link.

**The Positive Assignment Constraints:** The last constraint is to allow only positive values for $q^k_{i,j}$, to make it consistent with the directed links.

In the beginning, the system initializes the link costs based on the maximum speed for each link. Then, it uses the latest updated link information to periodically optimize the link-flow assignment. This interval is called the "Updating Interval", which is a system parameter. The link-flow assignment matrix is used to build stochastic routes when requested by a vehicle.

### C. Building Vehicle Routes

Upon receiving a route request from a vehicle, the TMC calls the route construction algorithm, shown in Algorithm 1. The route construction procedure takes four input parameters: the flow number $k$, the start node $s$, the destination node $d$, and the link-flow assignment $q^k_{i,j}$ for the $k^{th}$ flow. The algorithm stochastically creates a route as follows. It starts with the vehicle's source node $s$, and uses it as the current node $i$. Then, it finds all the links going out of this node $i$, the link set $\check{L} = \{L_{i,j} : L_{i,j} \in \mathcal{L}\}$. For each link $L_{i,j} \in \check{L}$, it computes $p_j = q^k_{i,j} / \sum_{L_{i,d} \in \check{L}} q_{i,d}$, which is the probability to select this link as the next link in the route. Then, based on the computed values $p_j$, the algorithm stochastically selects one of these links to be the next link and adds it to the route. Then, the algorithm uses its end node $j$ as the current node $i$, and repeats the process until reaching the vehicle's destination.

## V. Simulation and Results

The proposed model is developed within the INTEGRATION software [17] which is an agent-based microscopic traffic simulation and assignment framework.

INTEGRATION is characterized by its accuracy in estimating travel time because it replicates vehicle longitudinal motion using the Rakha-Pasumarthy-Adjerid (RPA) car-following model [18] which captures vehicle steady-state car-following behavior. It also accounts for traffic lights and their impact on the travel time. Moreover, its microscopic nature

**Algorithm 1**

**procedure** BUILD A VEHICLE ROUTE($k$,$q^k_{i,j}$, $s$, $d$ )
    $R \leftarrow \phi$
    $i \leftarrow s$
    **while** $i \neq d$ **do**
        $R \leftarrow (R, i)$
        $\check{L} \leftarrow L_{i,j} : L_{i,j} \in \mathcal{L}$
        **for each** $L_{i,j} \in \check{L}$ **do**
            $compute \quad p_j$
        $r \leftarrow randomnumber$
        **for** `j=1 to sizeof` $\check{L}$ **do**
            **if** $\sum_{\check{j}=1}^{j} p_{\check{j}} \leqslant r$ **then**
                $i \leftarrow j$
                $break$
    **return** $R$     ▷ Return the computed route.

enables it to accurately model vehicle queues and congestion which significantly affect the link travel time. The scalability of the INTEGRATION software enabled us to model up to 23,000 vehicles in the network scenario. We use the CPLEX Optimizer [19] to compute the the traffic assignment. To study the efficiency of the proposed framework, we compare it to the dynamic time-based traffic assignment which uses the shortest path routing based on the dynamic link travel times given that this would best reflect the state-of-practice routing.

We use the FIFA World Cup 2022 event which will be held in Qatar as a case study. After football matches, the number of vehicles that need to leave the stadium is huge, resulting in a vehicle crowd surrounding the stadium area. The following subsection describes the network and traffic demand setting.

### A. Network and Traffic Setup

To achieve realistic results, we used a real network with calibrated background vehicular traffic demands. The time-dependent static origin-destination (O-D) demand matrices were generated every 15 minutes using the QueensOD software [20]. QueensOD estimates the most-likely O-D matrix that is as close structurally as a seed matrix while at the same time minimizes the error between the estimated and field observed link flow counts.

The network shown in Fig. 1 is used for the simulation. It is a part of Doha city in Qatar where the FIFA World Cup 2022 will be held.

To build the simulation network, data were collected from different sources that include: 1) a road network Geographic Information System (GIS) Shapefile; 2) intersection data from OpenStreetMap (OSM); and 3) Google maps and ArcGIS. The Doha city shapefile was used to generate the network nodes and links. OpenStreetMap data were used to extract intersection traffic control information including the traffic control methods (stop sign, yield sign, or traffic signals). The number of phases for each traffic signal and traffic signal timing information were obtained based on field observation.Google maps and ArcGIS were utilized for validating road attributes including number of lanes, one-way streets, and speed limits for each road segment. The resulting simulation network has 169 nodes, 301 road segments, and 11 traffic signals.

We assume that the red area in Fig. 1 is a stadium from which vehicles belong to the controlled traffic (CT) will depart to different network points (as shown by the yellow arrows). This traffic is distributed over 10 network exit points. In regards to background traffic (BT), which represents the regular traffic traversing the network, it was calibrated using the technique [20] based on car counts data collected from the OpenStreetMaps (OSM) website. The BT rate in the first row ($S1$) in Table I is 10% of the calibrated traffic. In this scenario $S1$, we assume that there are 2800 cars as the CT. The rates in $S1$ is multiplied by scaling factors 2 through 5 to compute the higher traffic rates in $S2$ though $S5$. We assume that these vehicles should leave within one hour with uniform inter-departure intervals. This way, these car counts can be converted into traffic rates.

We tried to increase the traffic in $S5$, but the optimization failed to solve the LP problem because the traffic rate becomes higher than the network capacity.

### B. Evaluation Metrics

Our main objective is to minimize the network clearance time by minimizing network-wide travel time. So, we use the following two metrics: (1) ***Network Clearance Time*** is the time at which the last vehicle reached it destination and the network is completely cleared, and (2) ***Average Vehicle Travel Time*** is computed as the summation of all vehicles' travel times divided by the number of vehicles, i.e., $T_{av} = \frac{\sum_{v \in V} T_v}{||V||}$. The travel time for each individual vehicle $T_v$ is the time it takes from its scheduled departure time to the moment it reaches its destination.

### C. Simulation Results

We run each of the 5 traffic levels using both the Stochastic LP routing and the shortest path routing. To have statistically significant results, each scenario is run 16 times with different seeds and the average evaluation metrics are computed.

#### 1) Network Clearance Time

Fig. 5 compares the network clearance time for both the shortest path routing and the stochastic LP routing. It demonstrates that: (1) at low traffic demand levels ($S1$, $S2$), there is no significant difference between the two routing techniques at 0.05 confidence level, (2) for the higher traffic levels ($S3$, $S4$, $S5$), the proposed model reduces the network clearance time by (28%, 32%, 38%), respectively. These two findings demonstrate the importance of the proposed model in the case of large events or evacuation cases, which are the typical scenarios for which it is proposed.

#### 2) Average Vehicle Travel Time

We compute the average travel time for the BT and the CT individually, as well as the combined traffic as in Fig. 6. It is clear that for the CT, the stochastic routing is successful in decreasing the average vehicle travel time except for the lower traffic demand level ($S1$) where the CT travel time increased by around 17% as shown in Fig. 6-(a). The reason for this increase in the CT travel time is that for the low traffic rates, the network is not congested. And, in order to avoid causing congestion on the shortest paths, the stochastic LP

Table I: Traffic Levels.

| Scenario # | Controlled Traffic | Background Traffic | Total |
|---|---|---|---|
| S1 | 2800 | 1603 | 4403 |
| S2 | 5600 | 3383 | 8983 |
| S3 | 8400 | 5245 | 13645 |
| S4 | 11200 | 7127 | 18327 |
| S5 | 14000 | 9085 | 23085 |

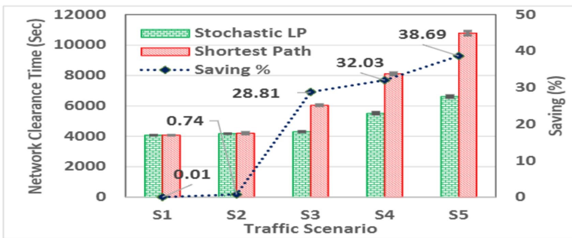
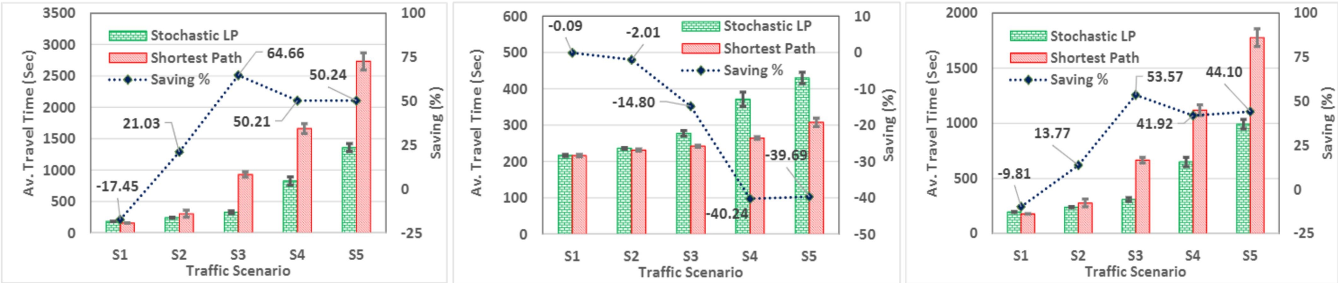



Fig. 5: Network Clearance Time




(a) CT only

(b) BT only

(c) CT and BT

Fig. 6: The Average travel time

routing assigns the CT vehicles longer routes that increases the travel time. While, in the higher traffic rates, the congestion level becomes higher and the shortest path becomes congested which makes the stochastic LP more beneficial.

Fig. 6-(b) shows that, applying the stochastic LP routing for the CT has a negative impact on the BT which uses the shortest path. The reason is that, applying the stochastic LP routing to the CT results in higher CT vehicle density in the network which reduces the available capacity for the other BT traffic. However, the average travel time for the combined traffic became better except for the lowest traffic demand level as shown in Fig. 6-(c).

## VI. Conclusion

In this paper, we utilize the vehicular communication network to propose a new framework for vehicle navigation in the case of large gathering events or evacuation cases. Vehicles are employed as sensors, and VANET is used as infrastructure to collect the network-state conditions in real-time. Then, linear programming is used to compute the link-flow assignment in order to minimize the network-wide travel time. Based on link-flow assignment, the routes can be stochastically assigned to vehicles. The micro-simulation of the proposed model shows that by the virtue of VANET communication, the proposed navigation system outperforms the regular shortest path navigation techniques in the case of high traffic demands.

A future extension for this work is to consider the communication network load and to study the communication requirements for such system to work efficiently. A second extension is to study the sensitivity of the proposed navigation system to the communication reliability.

## Acknowledgment

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