Vehicular Crowd Management: An IoT-Based Departure Control and Navigation System

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***Abstract*—Large sport and entertainment events such as soccer games or concerts attract an immense number of fans, most of whom use personal vehicles to get to the event. Such a large number of cars presents a "vehicular crowd" that needs to leave in an organized, timely, and safe manner after the event. Combining vehicular crowds with a constrained road networks raises the need for efficient techniques for vehicular crowd management which is a fundamental building block in smart cities. We introduce a novel Vehicle Departure Control (VDC) and navigation system to clear the network in a shorter time and reduce network congestion and system-wide travel time. The proposed system collects network information from a variety of sensory devices: connected vehicles, smartphones, and traffic cameras. Then, it fuses this data to compute the current state conditions of each road link. Based on these parameters, the VDC module determines the allowable vehicle departure rates, and the navigation module computes the system-optimum routes for drivers to take. The proposed system is implemented in a microscopic simulator. The FIFA World Cup 2022 is used as a case study. We compare the proposed system to the Sup-population Dynamic Time-dependent Incremental Traffic Assignment (SFDTIA) which is a typical real-time navigation system that is currently in use by commercial systems. The results show that our optimum navigation and departure control reduced the network clearance time on average by 16%, and by 37% in certain extreme conditions.**

***Index Terms*—IoT-based Navigation, Vehicle Departure Control, Stochastic Routing, Crowd Management**

I. Introduction

Sports and entertainment events at stadiums are examples where vehicular crowds occur in a limited area. The majority of attendees use personal vehicles to attend the event. Therefore thousands of vehicles (i.e., vehicular crowd) need to leave after the event, which may cause congestion if not smartly and efficiently managed.

Most cities are not designed to support this kind of high traffic volume which, in such cases, often exceeds the road network capacity [1], [2]. The massive traffic volume results in higher vehicle density on the roads. Consequently, and according to the fundamental relationship between speed and density [3], a lower average travelling speed and longer travel times are inevitable results. Additionally, the high traffic volume produces longer queues at signalized intersections, which increases the travel time. Moreover, in complex road networks, this may result in network grid-locks. These problems, which have been neglected so far in the research of smart transportation systems [4], raise the need for efficient and smart vehicular crowd management system, with traffic control and route planning capabilities to utilize the network facilities in a better way while maintaining certain performance levels.

The Internet of Things technology (IoT) [5] introduces new opportunities to improve vehicle mobility and remedy congestion problems in smart cities. IoT utilizes the advancement in communications, control, information processing, and computing systems to build integrated systems that collect, process, and analyze information from different sensors to assist in making better informed decisions.

By utilizing IoT, this paper introduces a novel vehicular crowd management system that integrates departure control and smart navigation, to better manage vehicular crowds after large gathering events. The objectives of the proposed system are to clear the network faster and to decrease the average travel time by reducing the network congestion.

A deeper look at these objectives shows that they contradict one another. Clearing the network faster means allowing vehicles to depart early after the event, while early departures may result in higher traffic rates, more substantial congestion, and longer travel time. On the other hand, reducing congestion means reducing vehicle departure rates (i.e., increasing the inter departure intervals), which results in longer clearance time.

The main idea of the proposed system is to compromise between the two contradicting objectives; the maximum allowable departure rates and minimum travel times. So, the system allows vehicles to depart as early as possible after the event, in such a way that does not increase the network congestion or negatively impact the network-wide average travel time.

To achieve this goal, the proposed framework collects data from three types of IoT sensors: connected vehicles, smartphones, and cameras installed at traffic lights. The collected information is fused to compute the network state information (travel time and traffic load on each road segment). Combining the network state information with traffic demand levels, enables the system to run its two main functions; **1) the Vehicle Departure Control (VDC)** which computes the allowable vehicle departure rates based on the current network condition, and **2) the stochastic system-optimum navigation** that aims

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to minimize the network travel time by simultaneously routing vehicles (going to the same destination) through multiple alternative routes. These two functions are integrated to avoid contradiction between them. The paper's contributions are:

- To propose a VDC system for vehicular crowds. This system is responsible for controlling vehicle departures to allow vehicles to leave as early as possible, while maintaining minimal congestion levels and minimum system-wide travel time. The VDC achieves this objective by computing the maximum allowable vehicle departure rates, based on the current road network state conditions and considering the capacities of the road links.
- The VDC system is integrated with the system-optimum navigation [6], [7] to minimize the network congestion by optimizing the use of the available capacities.
- The proposed system is developed within a microscopic simulator. Then, it is tested on a real road network with real calibrated traffic. As a case study, we use the FIFA World Cup 2022, to be held in Doha, Qatar. The Doha road network is implemented and used to compare our proposed system to the un-controlled cases.

The remainder of the paper is organized as follows. Section II explains the network model and its objectives. Section III describes the proposed system and its components. Section IV presents our case study on the Doha network, and its results before the conclusions in Section V.

II. Network Model And Objective

To describe the system's mathematical model, this section presents the network model and defines our objective.

A. Network Model

In our proposed model the road network is represented by a directed graph $\mathcal{G}(\mathcal{N}, \mathcal{L}, \mathcal{C})$, that has a sGet $\mathcal{N} = \{i : i = 1, 2, ..., n\}$ of n nodes and a set $\mathcal{L} = \{L_{i,j} : i, j \in \mathcal{N}\}$ of l directed links (road segment), where $L_{i,j}$ is the road segment from node i to node j. Each road segment is characterized by a capacity $C_{i,j} \in \mathcal{C}$ which is the maximum traffic flow rate that can enter this link without causing congestion in this segment. Each segment has a variable travel time $T_{i,j}$ that depends on the traffic conditions in each segment. Additionally, each road link has a time-varying traffic load $\zeta_{i,j}$ which represents the average vehicle rate passing it. Thus, the available capacity on each road segment can be computed as $C_{i,j} - \zeta_{i,j}$.

In Fig. 1, the vehicular crowd is represented by the red area. In our case study, this red area represents a stadium where matches are to be held. The stadium parking area has a set of gated exit points. Vehicles leaving this area towards different destinations distributed across the network. These vehicles are grouped into a set of Origin-Destination (OD) demand pairs based on their destinations (this traffic information is collected using smartphones as described later in Subsection III-A4). Each OD pair is a traffic flow from the stadium to a destination, shown by yellow arrows in Fig. 1.

Therefore, there is a set $\mathcal{F}$ of f O-D flows, each flow is identified by $k \in \{1, 2, ..., f\}$, and each has V_k vehicles that

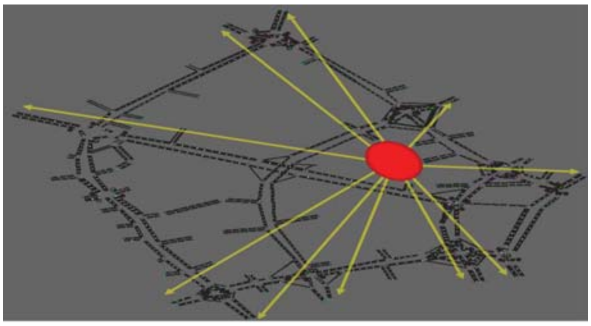

Fig. 1: The Network Model

need to leave within a time interval τ. Thus, each flow $k \in \mathcal{F}$ has a traffic rate $q^k = V_k/\tau$ (in vehicles per hour veh/h), this rate is calculated based on the information collected from the drivers and used as initial vehicle departure rate. Subsequently, and periodically, the vehicle departure rate will be updated by the VDC based on the network status.

By utilizing the smartphones or the vehicle's on-board communication systems, the Traffic Management Center (TMC) sends two types of control information to vehicles: 1) departure information from the VDC and 2) routing information from the navigation system. We call these traffic flows in $\mathcal{F}$ the Controlled Traffic (CT). In addition to CT, there is a Background Traffic (BT) which is the regular traffic traversing the network. Vehicles in the BT use the dynamic time-dependent best path routing.

B. Objective

Our objective is to clear the network as early as possible by using two techniques based on the current network conditions

The first technique is the Vehicle Departure Control (VDC) that computes the CT vehicles maximum allowable departure rates to avoid network congestion. The vehicle departure rates should not exceed the network maximum flow [8]; otherwise, it will cause longer travel time and network clearance time. Therefore, in the case of high traffic demand rates, the VDC will request some drivers to delay their departures by sending them notifications on their smartphones through the mobile application. Those drivers are selected based on their previously shown willingness to be delayed in the furtherance of the overall system performance.

The second technique is the stochastic system-optimum navigation that utilizes the network resources better by routing CT vehicles (going to the same destination) though multiple alternative routes at the same time in such a way that minimizes the network-wide travel time. Moreover, this optimized stochastic navigation contributes to reducing congestion because it balances the traffic across multiple routes.

Combining these two techniques allows vehicles to depart as early as possible (after the event), while minimizing network congestion, resulting in reasonably high average vehicle speeds, and clearing the network in a shorter time.

III. IoT-based Crowd Management Framework

IoT enables the integration of several technologies and communications paradigms including identification and tracking technologies, wired and wireless sensor and actuator networks, communication protocols, and smart devices [9]. Our proposed system utilizes IoT by integrating different sensors (connected cars, smartphones, and traffic cameras) and actuators (human drivers and autonomous vehicles) to enable better management of vehicular crowds.

The proposed framework and its components, including the data collection and processing, the optimization module, the departure control module, and the navigation module are described in this section.

The system architecture includes a front end and back-end subsystems. The front-end of the system is an application that can be installed on either the on-board computer or driver's smartphones. The car application is responsible for computing travel time that the car experiences on each road segment, and communicating this information to the TMC. Additionally, requests routes from the TMC. The smartphone mobile application has the same functionalities in addition to an interface to the departure control system. Through this interface, the user can set her/his destination and receives the departure control information as will be shown in Subsection III-D2. The back-end of the system is the TMC that has the components shown in Fig 2, which are described below.

A. Data Collection and Processing Module

In smart cities, the communication network enables the TMC to communicate with different network sensors/actuators to collect or disseminate information.

In our system, the TMC collects information from different sources, i.e., traffic information from connected vehicles and traffic cameras, and users' information from smartphones. These data are used to compute the network parameters required to manage and control the traffic. The proposed system needs to compute two parameters for each road segment $L_{i,j}$; the current travel time $T_{i,j}$ and the current traffic load $\zeta_{i,j}$. These parameters are integrated with the network graph information, such as the link capacities $C_{i,j}$, to optimize the vehicle departure rates and traffic navigation.

1) Data Collection and Privacy Preferences: In our system, all the CT vehicles will receive control information from the TMC (departure control and navigation). Due to privacy or other user preferences (such as network usage), some drivers

Fig. 2: System Components

may be reluctant to share their information with the TMC. The system front end application should allow each user to select her/his own privacy and preferences settings. To cope with this privacy preference of the drivers in our system, we assume that only some vehicles communicate their information to the TMC. We call those vehicles who share their information connected cars, while the others are non-connected cars. But, both of them receive navigation information from the TMC.

2) Traffic Information from Vehicles: Data collected from connected vehicles are used, along with other data sources, to continuously update the network state-conditions; $T_{i,j}$ and $\zeta_{i,j}$. To compute these parameters and in addition to vehicle connectivity, we utilize the vehicle Global Positioning System (GPS) (in connected vehicles and smartphones) through which a vehicle (or a smartphone) can identify which link it is traversing. Thus, whenever, a vehicle finishes a road segment, it computes the travel time it experienced on this segment $\widehat{T}_{i,j}$. Then, it builds a message with this information along with the current time as well as the next road segment ("$Next\_LinkID$") it will take. The vehicle then sends this message to the TMC. It can use V2I or V2V (i.e., car A and B in Fig. 2, respectively). If the car does not have a connection (such as car C in Fig. 2), it will store the message for a given time interval. If it reached a covered area it will try to send the message, otherwise the message will be dropped upon the expiry of the queuing interval.

Upon receiving a message, the TMC uses the information in the unexpired messages (based on the message timestamp) to update the link travel time information. It fuses the new information with the link history using exponential smoothing (we use an exponential smoothing factor $\alpha = 0.2$), as:

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

To estimate the total traffic load $\zeta_{i,j}$ on each road link, the TMC first computes the traffic load of the connected cars $\zeta^{c}_{i,j}$ and then fuses it with the information received from cameras.

To compute $\zeta^{c}_{i,j}$, the system uses the "$Next\_LinkID$" field in the received messages to count the number of connected cars entering a road segment. Then, it periodically computes the traffic volume of the connected cars on each segment, and smooths this rate with the link history.

3) Traffic Information from Cameras: To compute the traffic load $\zeta_{i,j}$ on each road segment, the connected car information is not sufficient because it counts only the connected vehicles while we need the total load $\zeta_{i,j} = \zeta^{c}_{i,j} + \zeta^{n}_{i,j}$ (connected vehicles load + non-connected vehicles load).

By applying image processing techniques on the videos from cameras, installed on some traffic lights, we can find the traffic load on road segments under surveillance by these cameras. However, these cameras do not cover all road links because there are many intersections without traffic lights, moreover, there are some traffic lights without cameras. So, the network is partially covered by cameras.

Thus, we use the data from both sources, connected cars and cameras, to overcome the shortcoming of both. We use a simple method to compute the total penetration ratio P as follows. Let $\hat{\mathcal{L}}$ be the set of observed links. For each observed links $L_{i,j} \in \hat{\mathcal{L}}$, we compute its total traffic load $\zeta_{i,j}$ based on the image processing to count cars entering these links. Therefore, we can compute the average market penetration ratio of the connected vehicles P as:

$$P = \frac{\sum\limits_{L_{i,j} \in \hat{\mathcal{L}}} \zeta^c_{i,j}}{\sum\limits_{L_{i,j} \in \hat{\mathcal{L}}} \zeta^n_{i,j} + \sum\limits_{L_{i,j} \in \hat{\mathcal{L}}} \zeta^c_{i,j}} \tag{2}$$

Then, we use P to compute the total traffic load on the non-observed links as:

$$\zeta_{i,j} = \frac{\zeta^c_{i,j}}{P} \tag{3}$$

4) Driver Destination Information and Traffic Loads: The distribution of driver destinations is the main information needed to compute the vehicle departure rates. This can be collected using the system front-end application (installed on smartphones or car's on-board computer system) that drivers use to set their destinations. Drivers also can indicate how long they are willing to wait after the event before leaving. To incentivize drivers to delay their departure after the event, the system can offer free or discounted tickets to future events based on the time they will wait. Other types of incentives include taking pictures with the event's public figures or signed simple gifts.

These two pieces of information (driver destinations and waiting time after the event) are used by the system to estimate the initial demand rates and then optimize the traffic assignment and departure rates.

B. The Optimization Module

The optimization module is a major part of the proposed system that controls both the vehicle departure rate and the navigation. The optimization module utilizes the linear problem described in our previous work [6], [7] to compute the traffic assignment and departure rates. For the sake of completeness, we will briefly describe the linear problem in this section.

1) The Optimization Problem and Constraints: The main idea behind the developed optimization model is to achieve the best utilization of the resources (road capacities) by using the under-utilized links in such a way that minimizes the network-wide travel time. For instance, if there is a flow of rate $q^k = 100\, veh/h$ between an origin and destination, and there are two alternative routes R1 and R2. Assuming the available capacities and the current travel times on these routes are $70\, veh/h$ and $10\, minutes$ for R1 and $50\, veh/h$ and $8\, minutes$ for R2. Then, instead of using only the best route (R2 in this case) and overloading it with twice its available capacity (which will results in congestion and increases its travel time), the model will divide the traffic across the two routes in such a way that minimizes the total travel time, meanwhile avoiding the congestion on both routes. Thus, in case of high traffic demand, the model inherently tries to achieve the maximum flow rate in a multi-origin multi-destination network, while maintaining the network-travel time minimal.

The linear problem minimizes the network-wide travel time by computing the link-flow assignment parameters $q^k_{i,j}$ for each link-flow pair. Vehicles in the k^{th} flow whose rate is q^k can be assigned different routes at the same time. The link-flow assignment $q^k_{i,j}$ is the portion of the k^{th} traffic flow that should go through $L_{i,j}$. The general idea of the linear program is to divide each flow rate across a set of alternative routes by computing $q^k_{i,j}$ that minimizes the network-wide travel time, while respecting the road capacities. The optimization problem is formulated as:

$$\begin{aligned}
&\underset{q^k_{i,j}}{\text{minimize}} \sum_{i=1}^{n}\sum_{j=1}^{n} T_{i,j} \sum_{k=1}^{f} q^k_{i,j}\\
&\text{subject to :}\\
&\sum_{d=1}^{n} q^k_{i,d} - \sum_{s=1}^{n} q^k_{s,i} = 0, \qquad \text{if } i \text{ is an intermediate node}\\
&\sum_{d=1}^{n} q^k_{i,d} - q^k = 0, \qquad \text{if } i \text{ is the source of the } k^{th} \text{ flow}\\
&q^k - \sum_{d=1}^{n} q^k_{s,i} = 0, \quad \text{if } i \text{ is the destination of the } k^{th} \text{ flow}\\
&\zeta_{i,j} + \sum_{k=1}^{f} q^k_{i,j} \leqslant C_{i,j} \quad \forall\ L_{i,j} \in \mathcal{L},\\
&q^k_{i,j} \geq 0.
\end{aligned} \tag{4}$$

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 linear program has three sets of constraints: route continuity, link capacity, and positive assignment constraints.

The **Route Continuity** constraints, represented by the first three constraints in Eq. 4, ensure that the computed traffic-flow assignment results in a connected route for each flow k from its origin to its destination. This is achieved by enforcing the individual flow balance at each node, which means that at every intermediate node, for each individual flow $k \in \mathcal{F}$, the summation of the vehicles (belonging to k) entering that node equals to the summation of the vehicles (belonging to k) exiting this node. For each source or destination node, we add or subtract the total flow rate q^k respectively.

The **Link Capacity** constraints avoid overloading any road segment more than its capacity. If the traffic demand rates exceed the network capacity, this constraint will not be satisfied. So, in this problem, it inherently tries to achieve the maximum flow rate in a multi-origin multi-destination network while maintaining the network-travel time minimal. Therefore, this constraint plays a major role in computing the maximum allowable vehicle departure rate for each flow.

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

C. Navigation Module

The optimized link-flow assignment $q_{i,j}^k$ is used to build routes for vehicles upon request. When a vehicle requests a route or a route update the navigation system uses the car's flow number k and its current location to assign it a route stochastically. From the car's location the system identifies its current road segment whose end node is used a current node i for this car. Then, for each link $L_{i,j}$ going out of this node i, the system computes the probability to select this link as the next link in the route as:

$$p_j = q_{i,j}^k / \sum_{L_{i,d} \in L} q_{i,d} \tag{5}$$

Based on P_j, the navigation module randomly selects one link as the next link. Then, it uses j as the current node i, and repeats the process until the vehicle's destination is reached.

D. Departure Control Module

The main objective of the VDC is to regulate the traffic leaving the event and entering the network to avoid network congestion. It does not allow vehicles to enter the network at rates higher than the maximum available network capacity. VDC play an important role when the traffic demand rates exceed the available network maximum flow rate. In such cases, the optimization module fails to find a solution for the LP problem. In order to find a solution for traffic assignment, the VDC needs to compute the maximum allowable traffic rates $\hat{q^k} \leq q^k$, and, accordingly, adjust the vehicle departure times. These are the two main functions of the VDC.

1) Computing the Maximum Allowable Traffic Rates: A straight forward solution to compute the allowable traffic rates is to use a multi-origin multi-destination maximum flow algorithms, such as [10], and apply it to the network using the current link traffic loads. However, this solution has two main drawbacks. First, it can result in a complete blockage of some traffic flows (i.e., setting $\hat{q^k} = 0$ for some flows) which violates the fairness among the traffic demands. Secondly, the computed traffic rates do not necessarily minimize the travel time since the maximum flow algorithms do not consider other metrics other than the capacities.

To maintain fairness and minimize travel time, the VDC aims to estimate the network maximum flow by reducing all the traffic demand rates by the same ratio, and then find if there is a feasible solution for the LP problem using these rates. It uses the optimization failure as an indication for high traffic demand. Consequently, bidirectional communication is established between the VDC and the optimization modules. When the optimization module fails to find a solution to the problem, it notifies the VDC, which decreases the demand rates by multiplying them by $r = 0.9$ and requests re-optimization using these reduced rates. This process is repeated until a solution is found. This solution satisfies the two objectives, fairness and minimum travel time. It is also less than or equal to the available network capacity. An advantage of this technique is that it is consolidated with the navigation system by using the same optimization problem, once we find a solution, its arguments are directly used by the navigation module to minimize the system-wide travel time.

2) Controlling Vehicle Departures: Once the VDC computed the allowable rate for each traffic demand, it adjusts vehicle departure times to match the new rates. The VDC uses a token-based model to control the departure of vehicles. So, if the departure time of vehicle v is computed to be D_v, the VDC sends it a token at time $D_v - T_p$, where T_p is the time needed by the driver to go to her car, to leave the parking lot and go to the gate at designated exit points (i.e., G1, G2, .. G5 in Fig. 2). When reaching the gate, the vehicle sends its token to the gate. The gates at exit points regulate the traffic heading to the roads based on the computed traffic rates. The importance of the gating is that drivers can reach the gates faster than expected. In this case the gate will not allow vehicles to exit until their departure times based on the token they have.

IV. Simulation and Results

To test the proposed model, it is developed within the INTEGRATION software [11] which is a microscopic traffic simulation characterized by its accuracy and scalability. To study the efficiency of the proposed framework, we compare it to the dynamic time-based incremental traffic assignment state-of-practice routing which uses the shortest path routing and achieves load-balancing among routes that similar in cost.

A. Network and Traffic Setup

The FIFA World Cup 2022 to be held in Doha, Qatar is used as a case study. The Doha network shown in Fig. 1 is implemented and used for the simulation. To build the network, different data sources are used. The Doha city shapefile is used to generate the network nodes and links. OpenStreetMap data is used to extract intersection traffic control information, including the traffic control methods (stop signs, yield signs, or traffic signals). Google maps and ArcGIS are utilized for validating road attributes, including the 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.

In the network shown in Fig. 1, the red area is a stadium from which CT vehicles will depart to different network destinations (as shown by the yellow arrows). The Background Traffic (BT) is calibrated using the technique in [12] using car counts data 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 CT cars. The rates in $S1$ is multiplied by scaling factors two through five to compute the higher traffic rates in $S2$ through $S5$. Assuming the drivers departure times are uniformly distributed over one hour, these car counts can be converted into traffic rates.

B. Simulation Results

Each of the five traffic scenarios was run using the SFDTIA, Stochastic Linear Programming System-Optimum (Stochastic LP), and Stochastic LP with VDC. Each scenario is run 16

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

times with different seeds, and the average evaluation metrics are computed.

1) Network Clearance Time: Network clearance time is the time at which the last vehicle reaches its destination and the network is completely cleared. Fig. 3 compares the network clearance time for the three cases. It shows that for low traffic demand levels ($S1$, $S2$), the stochastic LP has no significant impact on the network clearance time. While when applying the VDC, the network clearance increases by 1.3% and 2.16% for $S1$ and $S2$, respectively. It also shows significant saving in the clearance time for the more congested cases, which demonstrates the importance of the model in the case of large sporting ans entertainment events.

2) Average Vehicle Travel Time: Average vehicle travel time is computed as the summation of all vehicles' travel times divided by the number of vehicles, i.e., $T_{av} = \frac{\sum_{v \in V} T_v}{||V||}$. Fig. 4 compares the average travel time for the three cases. It shows that for scenario $S1$, the Stochastic LP increases the average travel time by approximately 14% and adding the VDC reduced this increase to only 6.2%. The reason for this increase is the sensitivity of the proposed system to network congestion. If any road segment becomes more congested, the stochastic LP navigation disperses the vehicles to longer routes which increase the travel time for those cars. Because, VDC tries to reduce congestion by reducing the traffic rates

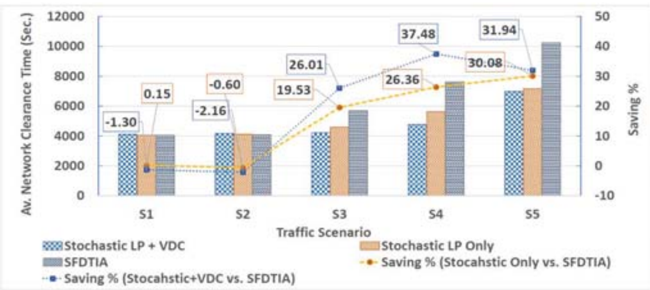

Fig. 3: Network Clearance Time.

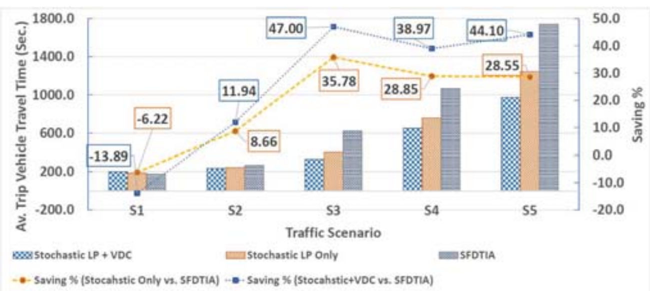

Fig. 4: Average Travel Time.

and consequently deferring the car departures, it mitigates this problem and reduces the number of cars that use the longer routes, thus reduce the average travel time. Finally, Fig. 4 shows the improvement achieved by the stochastic LP and that by VDC that reached about 47% reduction in total average travel time.

V. Conclusion

In this paper, IoT technology is utilized to build an efficient vehicular crowd management system that includes an optimum vehicle navigation and departure control schemes. The system collects information from connected vehicles, smartphone and cameras to compute the network parameters, which are used to optimize the navigation and departure control. The micro-simulation of the proposed model illustrates the significance of the proposed model in the case of a large gathering or in the evacuation cases, where it reduced both the network clearance time and the average vehicle travel time in the congested scenarios. A future extension for this work is to study the sensitivity of this system to the penetration ratio of the connected cars. Another extension is analysing the impact of the controlled traffic on the background traffic, and how to mitigate these negative impacts.

References

[1] X. Zhang, Q. Zhong, and Q. Luo, "Evaluation of transportation network reliability under emergency based on reserve capacity," *Journal of Advanced Transportation*, 2019.

[2] X. Zhao, M. jie Feng, H. ying Li, and T. Zhang, "Optimization of signal timing at critical intersections for evacuation," *Procedia Engineering*, vol. 137, pp. 334 – 342, 2016, green Intelligent Transportation System and Safety.

[3] N. Geroliminis and C. F. Daganzo, "Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings," *Transportation Research Part B: Methodological*, vol. 42, no. 9, pp. 759 – 770, 2008.

[4] A. Boukerche and R. W. Coutinho, "Crowd management: The overlooked component of smart transportation systems," *IEEE Communications Magazine*, vol. 57, no. 4, pp. 48–53, 2019.

[5] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future generation computer systems*, vol. 29, no. 7, pp. 1645–1660, 2013.

[6] A. Elbery, H. S. Hassanein, N. Zorba, and H. Rakha, "VANET-Based Smart Navigation For Emergency and Special Events," in *2019 IEEE 24th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD)*, Sep. 2019.

[7] A. Elbery, H. Hassanein, N. Zorba, and H. Rakha, "VANET-based Smart Navigation for Vehicle Crowds: FIFA World Cup 2022 Case Study," in *2019 IEEE Global Communications Conference: Selected Areas in Communications: Internet of Things (Globecom2019 SAC IoT)*, Waikoloa, USA, Dec. 2019.

[8] A. Schrijver, "On the history of the transportation and maximum flow problems," *Mathematical Programming*, vol. 91, no. 3, pp. 437–445, Feb 2002.

[9] L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," *Computer Networks*, vol. 54, no. 15, pp. 2787 – 2805, 2010.

[10] G. Borradaile, P. N. Klein, S. Mozes, Y. Nussbaum, and C. Wulff-Nilsen, "Multiple-source multiple-sink maximum flow in directed planar graphs in near-linear time," *SIAM Journal on Computing*, vol. 46, no. 4, pp. 1280–1303, 2017.

[11] H. A. Rakha, K. Ahn, and K. Moran, "Integration framework for modeling eco-routing strategies: Logic and preliminary results," *International Journal of Transportation Science and Technology*, vol. 1, no. 3, 2012.

[12] H. A. Rakha, H. Paramahamsan, and M. V. Aerde, "Comparison of static maximum likelihood origin-destination formulations," in *Transportation and Traffic Theory: Flow, Dynamics and Human Interaction*, 2005, pp. 693–716.