Toward a lightweight and efficient UAV-aided VANET

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Abstract

Connectivity in a smart vehicular network is quite sensitive and highly affected by its dynamic network topology. Issues related to the intermittent nature of connectivity may arise due to the high mobility of nodes and network heterogeneity. In sparse areas, a vehicular network is basically a disruption-tolerant network suffering from frequent disconnections, long delays, and messages loss. Facing these issues, and specifically for time-sensitive applications, Unmanned Aerial Vehicle (UAV) can provide valuable assistance to Vehicular Ad Hoc Network (VANET) by assuming a relay node role between disconnected segments in the road. In such scenarios, effective communication is either between vehicles (V2V) or between vehicles and UAVs (V2U), which would form subsequently a UAV-assisted vehicular network. In the present paper, we propose a new framework for using small UAVs as mobile infrastructure nodes in order to enhance the connectivity between vehicles. The first part of this framework accurately predicts the disconnected segments such that drones can be deployed to reestablish lost links. We have implemented a theoretical game for this prediction process. Furthermore, since the battery reserves of the UAVs are limited, we have proposed a mitigation technique based on game theory to reduce the power draining effects that a broadcast storm would have on the energy consumption of the network. For the validation of the proposed UVE (UAV-aided VANET framework, with energy-conscious constraints), we conducted thorough simulation scenarios with Network Simulator 3. The obtained performances are promising in the sense that our approach achieves high packet delivery ratio, low end-to-end delay, and low overhead communication costs.

1 | INTRODUCTION

Over the past few years, many research laboratories in industry and academia have been focusing their resources toward the development of sustainable communication networks adapted for vehicular networks. These networks present some unique characteristics such as long transmission delays and frequent disconnections. As a consequence, a vehicular network is perceived as a delay/disruption-tolerant network (DTN), which is characterized by the intermittent nature of connectivity, long transmission delays, and frequently lost packets.[1,2] These characteristics are particularly more significant in sparse networks and low-density regions.[3]

DTNs are known to provide communication capabilities in situations with long or variable delays and high transmission error rates, which are just some of the wireless networks issues.[4] Nevertheless, existing routing protocols, which use

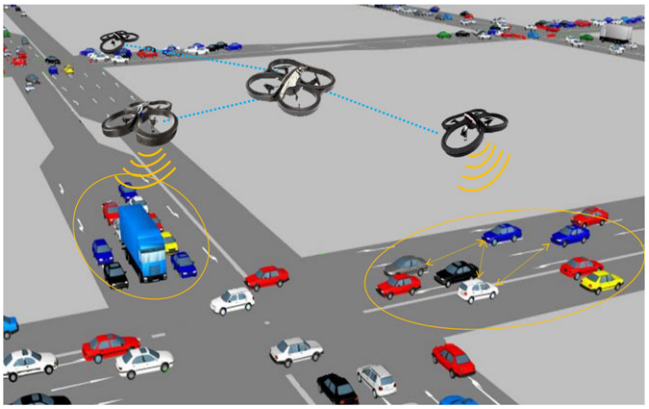


FIGURE 1 A synoptic scheme for the targeted heterogeneous network

opportunistic message delivery mechanisms, are not suitable and do not cope so well with the impracticalities posed by the high mobility of vehicular networks compared to traditional networks. Consequently, to overcome these irregularities, other solutions have been proposed in the literature. One of the adopted solutions was to implement an asynchronous communication model and message replication techniques to maximize the probability of data delivery to the destination.[5] Therefore, by taking the DTN paradigm into the mobile world, vehicular networks address the node density issue by providing means for an asynchronous data exchange similar to DTNs protocols. The main idea is to implement "store and then carry forward" the received packets throughout the intermediary entities/nodes.[6] Even though this approach is known to improve the overall connectivity and lost packets rate, newer and more demanding applications require even better network availability. In this context, the use of a dedicated static or mobile infrastructure to enhance vehicular networks connectivity is revealed to be quite essential.

Even though the use of static infrastructure such as Roadside Units (RSUs) permits attaining the best possible network performances, and in most cases, they are not a realistically feasible choice due to their deployment and maintenance cost. Furthermore, infrastructure deployment is nontrivial, requiring careful investigations in order to put the right devices in the right places. Therefore, mobile infrastructure nodes are more suited to overseeing the relaying of messages between vehicles nodes. Recently, achieved technological breakthroughs have allowed the emergence of an all new span of mobile devices, such as mobile ground stations and drones, that can be adopted as mobile infrastructure,[7,8] as illustrated in Figure 1. Drones, also known as Unmanned Aerial Vehicles (UAVs), are flying aircraft that do not require a human pilot onboard. This type of small aircraft can either be controlled remotely or autonomously. UAVs are commonly recognized for their usage in military applications. Large drone platforms are playing increasingly prominent roles in strategic and defense programs while technological advances in recent years have led to the emergence of smaller, significantly cheaper UAVs. These latter advances made the technology easier to acquire, maintain, and handle. Consequently, their usage has significantly increased and they have expanded in different fields of applications where they have proved to be quite useful not only in military applications but also in civilian applications such as research and rescue missions (earthquake), target detection, remote sensing and performing surveillance, and agricultural tasks. In these applications, drones sometimes carry out exploration missions in remote places to replace human presence and/or deliver data to and from areas with no infrastructure.[9]

In this work, we exploit this concept of using UAVs as mobile infrastructure nodes to enhance the connectivity in an already deployed vehicular network. Even though the general idea has already been covered in the literature,[7,8,10] a lot of challenges still remain. As illustrated in Figure 2, to ensure an efficient UAV-assisted Vehicular Ad Hoc Network (VANET) a couple of solutions should be developed, as follows. (i) Mobility: the movement of a UAV incurs certain energy consumption. Several optimal UAVs' mobility models are proposed to address this issue.[11,12] (ii) Prediction of vehicles location and disconnected segments: the UAV is deployed as mobile infrastructure to link between two disconnected vehicular networks, and hence, the transmission delays and the frequently lost packets are decreased. (iii) Channel characterization: according to the work of Zhou et al,[10] the propagation channel model developed for VANET is not suitable for UAV networks since it could impact the coverage capacity of the UAV-aided VANET and UAV energy efficiency. Therefore, a reliable propagation channel model that takes into account the requirements of UAV-aided VANET such as energy, coverage and nodes' mobility should be developed. (iv) Communication overhead: to predict the optimal deployment of UAVs to serve as relay nodes between vehicles requires a certain data to be exchanged between UAV and vehicles. In cases where

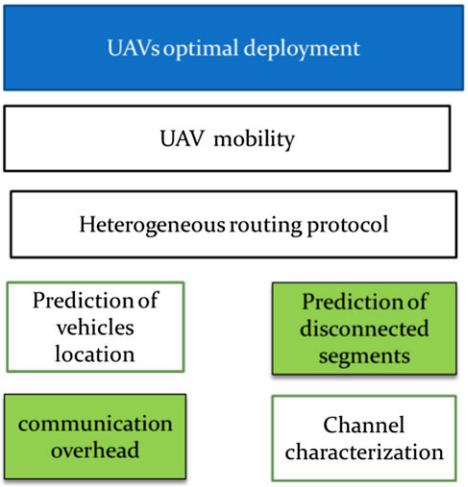


FIGURE 2 An efficient UVE. UAVs, Unmanned Aerial Vehicles

the amount of data increases, a high communication overhead could be generated, and hence, this leads UAV to exhaust its energy resources. (v) Heterogeneous routing protocol: the routing protocol of this heterogeneous network uses a couple of routing metrics from both VANETs and UAVs networks to switch dynamically between communication technologies used by vehicle and UAV.

Our major focus in this research work is to address two issues in this framework, namely, the prediction of disconnected segments and the communication overhead. Hence, we aim first to predict the possible disconnected segments, so that we can deploy UAVs to guarantee the connection between them, while taking their energy constraints into account. The decision-making process is modeled and implemented through a game theory approach. Second, another major issue is addressed in this paper, which is related to the broadcast storm undermining effect, because the process of accurately predicting the advent of disconnected segments requires exchanging an important number of packets. Thereby, in this research work, we propose a broadcast storm mitigation technique to undermine the draining effect that this problem could have on the energy consumption of UAVs and, thus, the UAVs lifetime.

Regarding the mobility model, channel characterization model and heterogeneous routing protocol, readers are referred respectively to the works of Oubbati et al,[7] Zhou et al,[10] and Messous et al.[12]

The rest of this paper is structured as follows. In Section 2, we highlight the most notable research papers that influenced our work, while in Section 3, we present the network architecture. Then, in Section 4, we give the detailed mathematical modeling and the corresponding proofs of the two primal contributions of this paper: the prediction of disconnected segments and the broadcast storm mitigation technique. In order to evaluate the achieved performances of our solution, the experimental results, along with their interpretation, are provided in Section 5. Finally, Section 6 concludes this paper and summarizes the major findings of our work.

2 | RELATED WORK

Several previous works have addressed the issue of DTNs in vehicular networks.[2,7,8,10,13-16] In these works, they propose an opportunistic vehicular network composed of vehicles and assisted by a set of infrastructures. These infrastructures assume a relay role for packets when no neighboring vehicles are available. Mehar et al,[2] Aslam et al,[13] and Sun et al[14] use static RSUs as relays to enhance the end-to-end delay and decrease the packet dropping ratio (PDR). Specifically, Mehar et al[2] focus on finding the most appropriate locations for erecting RSUs based on traffic density and vehicular connectivity. RSUs should be placed in zones where vehicles cannot reach and communicate with each other, ie, sparse network. To reduce communication delays and, at the same time, decrease the infrastructure deployment cost, finding the best RSUs location is done with a combination of genetic heuristic[17] and Dijkstra's algorithms.[18] Simulation results show that the proposed approach ODEL (Optimized RSU Placement for DTN Applications in VANET) deals well with a delay-sensitive VANET application. This approach reduces the delay and deployment cost by up to 84% and 23%, respectively. Static deployment of RSUs cannot guarantee a low end-to-end delay all the time. Therefore, relocating RSUs

can be required rather frequently, which may eventually lead to a considerable increase in the final deployment cost. In order to remedy this problem, a mobile infrastructure, with data forwarding support, could offer the best solution to overcome the issue of deployment cost increase and guarantee full coverage. Kim et al[15] investigated the optimal deployment of various types of RSUs on a metropolitan area while taking a limited budget into account. They considered three different deployment scenarios: (i) a static deployment, (ii) mobile deployment with no control on mobility, and (iii) and deployment of fully controllable mobile RSU. They modeled the problem as an optimization problem to find the best possible deployment of RSUs under a limited budget. The proposed solution was based on an approximation algorithm and the achieved performances were a 50% improvement over the previous solution. Consequently, a better performance ratio could be achieved with more work.

In the works of Oubbati et al,[7] Wang et al,[8] and Zhou et al,[10] a UAV-assisted VANET is proposed, where UAVs are used as a mobile infrastructure overflying sparse areas in order to relay data when connectivity between vehicles is not available. Specifically, in the work of Oubbati et al,[7] a UAV-aided routing protocol (UVAR) is proposed. In this protocol, the UAVs periodically collect information about network connectivity and the distribution of the nodes from vehicles located at each intersection. This information is then used by the UAV to place itself in disconnected segments (ie, if connectivity between vehicles is not available). Their simulation results outperform the current VANET's routing protocols in terms of packet delivery ratio and end-to-end delay. However, the major weakness of this research work is that the authors do not take into account the energy constraint of drones since at each intersection, an important number of vehicles broadcast a huge amount of data (ie, broadcast storm) to UAVs. This leads to an increase in the network overhead, which can eventually undermine the drones' energy, thus decreasing its average lifetime. In addition, this broadcast storm would lead to severe interference and a high number of packet collisions at the UAV level, which causes false detections of disconnected segments by UAVs. In the work of Wang et al,[8] the vehicles cooperate between each other to predict the location of destination vehicles. In this protocol, each vehicle collects the Global Positioning System (GPS) coordinates from its neighboring vehicles in order to feed a database for localization data and determine the future location of a target vehicle. In this proposed solution, vehicles use quadrotor drones to enhance the V2V transmission packets. In this context, UAVs are required to achieve different tasks: (i) collecting positioning data for predicting vehicles' locations, (ii) taking part in multihop packet forwarding as a relay node, and (iii) delivering messages directly to their destination. The performance analysis shows that using drones as relay not only has improved the packet delivery rate but also reduced the global end-to-end delay. Oubbati et al[7] do not take into consideration the energy constraints of the drones. This parameter is crucial, as high energy is consumed every time a message is collected, forwarded, or delivered to a target vehicle. Another interesting work was proposed by Zhou et al,[10] where the authors design a multi-UAV-aided vehicular network in which a UAV network and a VANET are fused together in order to improve the performance of the already existing VANET. In this proposal, UAVs would be sent to an area of interest to collect some data and eventually transmit it to ground vehicles. Additionally, UAVs can also act as intermediate relays when network partitions occur. The potential applications were research and rescue in a disaster zones or polluted areas. The major drawback of this work is the lack of a partition recovery mode and how to predict and handle the occurrence of a partition in the network. The authors did not address the problem of finding the optimal placement for UAVs when they are supposed to act as a relay node in disconnected areas. Patra et al[16] propose to use a mobile femto access point as a relay in order to enhance delay and throughput in VANET. In addition, they propose a power control algorithm to handle the interferences caused by the high mobility of vehicles. The performance of this solution is analyzed with and without the presence of LTE cellular network by computing the delay, throughput, and energy efficiency. Even though this approach has achieved a high packet delivery ratio and low end-to-end delay, it required a very high deployment and maintenance costs of the used infrastructures, ie, eNodeB.

In Table 1, we compare the different approaches discussed above, based on the following criteria:

- the different type of infrastructures;
- the relocation frequency of infrastructure;
- the energy consumption;
- the consideration of energy constraints;
- the improvement brought by the approach to the end-to-end transmission delay;
- the achieved performance in terms of packet delivery ratio.

Our approach deals with the drawbacks mentioned above. In this research work, we aim to predict the disconnected segments so that UAVs can be placed properly in order to ensure relaying data when direct connectivity between vehicles is not available, while taking into account the energy constraints of UAVs.

TABLE 1 Comparison between different infrastructures-assisted Vehicular Ad Hoc Network

Reference	Infrastructure	Relocation of Infrastructure	Relocation frequency of Infrastructure	Energy Constraint	Energy Consumption	Delay	Packet Delivery Ratio
12	Static	Yes	High	No	/	Medium	Medium
13	Static	Yes	High	No	/	Low	/
14	Static	Yes	High	No	/	Low	Medium
15	Static/Mobile	Yes	Medium	No	/	Low	High
7	Mobile	No	/	Yes	High	Low	High
8	Mobile	No	/	Yes	High	Low	High
10	Mobile	No	/	Yes	Medium	Medium	Medium
16	Mobile	Yes	Low	No	/	Low	High

In this research work, we consider a search and rescue scenario in a DTN, in which the intermittent connections and network partition occurred frequently. In this scenario, the LTE infrastructures could be destroyed by a natural disaster (eg, earthquake). Therefore, it is required to set up an emergency network, such as the UAVs network, which play the role of relay between the ground vehicles and between the ground vehicle and LTE infrastructure.

3 | NETWORK ARCHITECTURE

Vehicular networks (VANETs) are known to be a promising enabling technology for multiple services. Subsequently, they can provide safety-oriented and infotainment-oriented applications.[6] Safety applications involve critical time-sensitive requirements, which may provide real-time traffic management services and traffic jam prevention. While infotainment applications such as video on demand consist of commercial services that are more affected by the available bandwidth, which makes this kind of service bandwidth-oriented rather than for delay-sensitive applications. In sparse areas, VANET is basically a DTN suffering from frequent disconnection, long delays, and packet loss.[19,20] UAVs can provide valuable assistance to vehicular networks through acting as a relay node between disconnected segments that helps dealing with the aforementioned issues. In such a scenario, effective communication is either between vehicles (V2V) or between vehicles and UAVs (V2U), which becomes a UAV-assisted vehicular network. Based on the "store, carry, forward" mechanism,[6] DTN is used to decrease the packets loss and reduce the end-to-end delay. Furthermore, if neither a neighboring vehicle nor a UAV are currently available, data are stored in the vehicle buffer until a neighboring node becomes available.

As illustrated in Figure 3, each street has a disconnected segment represented by J_j, where $j = \{1, \ldots, k\}$ and k is the number of disconnected segments within the network. The disconnected segment J is defined as follows: N_{street}, C_{source}, and $C_{\text{destination}}$, where N_{street} is the street number and C_{source} and $C_{\text{destination}}$ are the GPS coordinates for the beginning and the end of segment J_j, respectively.

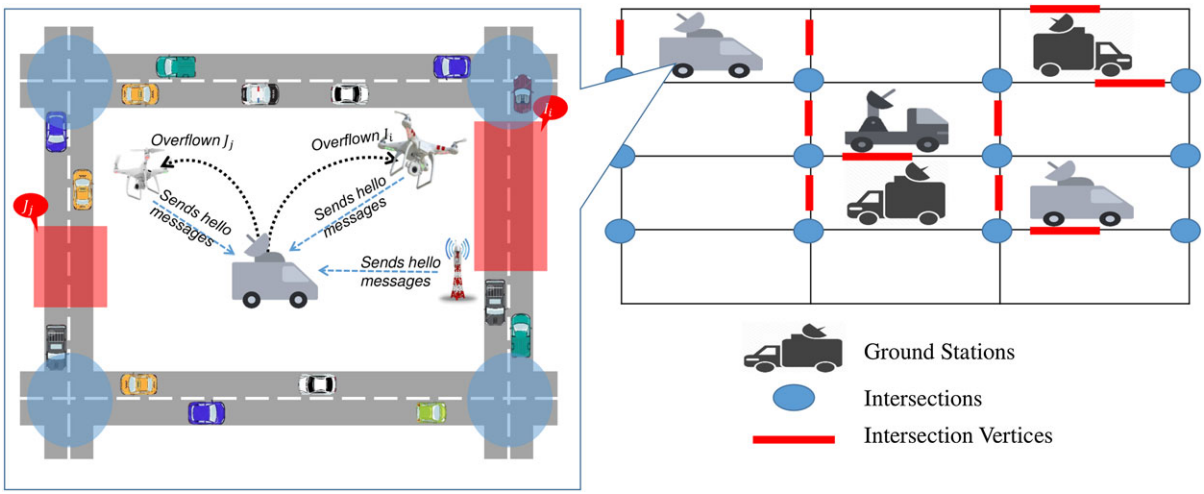


FIGURE 3 Network architecture

The ground station collects the traffic information of the vehicular network using periodic beacons (ie, hello messages). Moreover, with the help of our prediction game detailed in Section 4, the ground station orders a designated UAV to fly over the disconnected segment J_j to play a relay node role, as depicted in Figure 3. The hello messages contain the following information: GPS coordinates of the vehicle, the list of its neighboring vehicles with their coordinates, and then finally, the targeted destination. Three ways are possible for gathering traffic data: (i) Vehicle to Ground (V2Gr), (ii) Infrastructure to Ground (I2Gr), and (iii) UAV to Ground (U2Gr).

In V2Gr, each vehicle sends hello messages to the ground station within its radio range through an 802.11p interface. This mode allows the ground station to predict the disconnected segments with a high accuracy due to the considerable amount of received data. However, a high communication overhead could arise as consequence. The I2Gr model, 4G LTE would offer a communication medium to improve some VANET's challenges, such as delay and packet loss, due to the high LTE bandwidth and large area of coverage.[16] However, as indicated in the related work section, it is not wise to use the LTE infrastructure (eNodeB) as a relay since the frequent relocations of eNodeB is required to address the issues of packets loss and end-to-end delay. Therefore, the eNodeBs are used only as collector nodes to gather the hello messages from vehicles (within its radio range) and deliver these messages to ground stations via LTE for the disconnected segments' prediction as shown in Figure 3. Finally, U2Gr is intended for areas with no 4G LTE coverage and V2Gr communication.[21] In practice, this can translate to environments without network coverage such as disaster areas or rural regions with limited or no infrastructure. In this case, a set of UAVs can be deployed as collector nodes. These UAVs are launched from ground stations to carry out data gathering tasks. For instance, the UAVs fly over the intersections segments I_i, where $i = \{1, \dots, 4\}$ to collect the hello messages (see Figure 3) from vehicles and deliver them to ground stations, via a 802.11a interface, for the disconnected segments' prediction. The data gathering time for each UAV depends on its remaining energy level. When the energy level reaches a critical threshold while gathering data, the UAV must return to its initial ground station in order to deliver the hello messages and recharge its battery. To optimize the energy resource of the deployed drones, we propose throughout this paper a broadcast storm mitigation technique, whereby only an optimal number of vehicles are selected to send their hello messages to the UAV. The proposed technique is detailed in Section 4.2.

As shown in Figure 3, we deploy the ground stations in regions suffering from partial coverage due to the limited number of vehicles. In order to achieve optimal deployment, we use a graph-based model to select the best possible placement position for ground stations. For more details on the model used, we refer the reader to see the work of Sedjelmaci et al.[22] Our aim is to determine a low degree of intersection vertices (see Figure 3), ie, a region with a low distribution of vehicles, where the ground stations are deployed to request the UAVs to play the role of relay nodes and hence help forwarding data in case the next-hop vehicle is unavailable. The segment J_j, toward which a drone is required to fly, is determined with the help of the prediction game we are proposing. The details of this are provided in Section 4.1.

For the implementation of our UAV-assisted VANET system, the following assumptions are considered.

- Each UAV is equipped with GPS for positioning and locating the segments J_j and I_n to fly over/cover.
- The vehicles use GPS in order to determine the shortest path to their destination.
- UAVs have a limited onboard battery as a source of energy, which can be recharged as needed.
- Two distinctive modes of communications are possible: (i) *local mode* where a vehicle exchanges its hello message with another vehicle when they meet and (ii) *global mode* when vehicle communicates its hello message to the UAV.

4 | UAV-ASSISTED VANET

Throughout this research work, our aim is to predict the occurrence of disconnected segments in order to place UAVs as relay nodes while taking into account their limited energy. We model the proposed solution via a noncooperative mixed-strategy game theoretic approach. To the best of our knowledge, this is the first work that deals with the issue of UAV-aided vehicular network, while considering the energy constraint of the UAVs. In this section, we first present our prediction game to determine when disconnected segments could actually occur. In the following section, we propose a communication game model that aims to handle the issue of broadcast storm and hence increase the lifetime of UAVs.

4.1 | Prediction of disconnected segments

Current research studies[8,23,24] proposed prediction techniques for possible future trajectories of vehicles. Their prediction approaches use mostly the history of previous locations in order to select the shortest path for the vehicles to follow. These

techniques exhibit a high communication overhead since each vehicle is required to obtain the location of its neighboring vehicles, evolving in the same road segment, in order to determine the shortest path to the destination. As a consequence, severe interference and a high number of packets collisions can occur. In order to address these issues, we propose an efficient prediction technique based on game theory to predict the disconnected segments and, hence, request the UAVs to fly over these segments in order to play the role of relay node.

As explained previously in Section 3, the UAVs are launched from ground stations. The process of disconnected segments' prediction is launched at each ground station to predict which segment J_j will be covered by UAV u_i in order to enhance the vehicular network connectivity. In this case, the requested number of UAVs depends on the number of disconnected areas J_j. In this study, we assume that the ground stations are able to communicate with each other using professional digital mobile radios, such as TETRAPOL.[25] Therefore, to achieve a global view of the network, hello messages ought to be exchanged among ground stations using this means of communication. The formulation of a theoretical game predicting the process of disconnected segments is given as follows.

In our prediction game, we consider N players of UAV u_i; where $i = \{1, \ldots, N\}$. The overall objective of this game is to find an optimal solution that satisfies the network requirements, ie, low end-to-end delay and the minimization of battery consumption by the UAVs. Each u_i has a set of n possible strategies that u_i can eventually carry out $\varphi_{u_i} = \{\Omega_j | j = 1, 2, \cdots, n\}$. We define u_{-i} as all other players excluding player u_i and φ_{u-_i} as the set of their respective strategies. The strategies of players are defined as $\{(J_1, H_1), \ldots, (J_n, H_n)\}$, where J is the selected segment to be overflown by u_i and H is the direction. Let x_j be the probability that the player u_i adopts the strategy (J_j, H_j), and y_j be the probability that the player u_{-i} adopts the strategy (J_j, H_j), where $\sum_{j=1}^{n} x_j = 1$ and $\sum_{j=1}^{m} y_j = 1$. In addition, X and Y denotes the probability distribution vectors as $X = \{x_1, x_2, \ldots, x_n\}$ and $Y = \{y_1, y_2, \ldots, y_m\}$.

The payoffs M_i of each UAV player u_i (or u_{-i}) is defined as follows. (i) When the ground station predicts the correct disconnected segment J_j that need to be covered by UAV, ie, V2U communication, the payoff M_i is increased as shown in Equation (1). (ii) As shown in Equation (2), the payoff M_i will be decreased in cases where a connected segment is being overflown by UAV. (iii) The payoff M_i will be decreased in case no UAV overflows a disconnected segment J_j as shown in Equation (3).

$$M_i = ED_i - E_i \tag{1}$$

$$M_i = -(EN_i - E_i) \tag{2}$$

$$M_i = -EP_i \tag{3}$$

$ED_i \in [0,1]$ is the expected detection rate of disconnected segments, $EN_i \in [0, 1]$ is the expected false-negative detection rate (ie, a connected segment being recognized as a disconnected one), $EP_i \in [0, 1]$ is the expected false-positive detection rate (ie, a disconnected segment being recognized as a connected one), and $E_i \in [0, 1]$ is the required energy of the UAV to overfly a disconnected segment J_j. When $E_i = 1$, the UAV consumes almost all its energy and it cannot fly over the segment J_j. In this case, the remaining energy is used by UAV to return back to its initial ground station to recharge its battery.

The aim of player u_i is to maximize its payoff M_i by choosing the best strategy, ie, J_j being overflown by u_i with a direction H_j. In this case, the player u_i does not change their strategy regardless of the strategies of other players u_{-i}. This stable state of player u_i is defined as *Bayesian Nash equilibrium* (BNE), which represents the couple (x_j^*, Ω_j^*).

By collecting the hello messages from vehicles and with the help of *BNE*, each ground station tries to learn the paths that vehicles follow and hence predict the disconnected segment J_j to be covered by u_i, ie, determine (x_j^*, Ω_j^*).

Lemma 1. *Let $\mu(\Omega_j, \Omega_{-j})$ denote the total payoff of the game, where $\mu(\Omega_n, \Omega_{-n}) = (M_n, M_{-n})$. A pair of strategies Ω_j^* and Ω_{-j}^* is a BNE solution if the following inequality is satisfied:*

$$\mu\left(\Omega_j^*, \Omega_{-j}\right) \leq \mu\left(\Omega_j^*, \Omega_{-j}^*\right). \tag{4}$$

There is at least one BNE solution $\mu(\Omega_j^*, \Omega_{-j}^*)$ that satisfies inequality (4).

Proof. To find the *BNE* solution, the total payoff of the games is calculated by computing the sum of all payoffs M_j or M_{-j}.[26] The total payoffs of the players u_i and u_{-i} are defined in Equations (5) and (6), respectively.

$$\mu\left(\Omega_j\right) = \sum_{j=1}^{n} x_j * M_j \tag{5}$$

$$\mu\left(\Omega_{-j}\right) = \sum_{j=1}^{m} y_j * M_{-j} \tag{6}$$

The payoffs M_j and M_{-j} could increase and decrease depending on the strategy adopted by the players u_i and u_{-i} as shown in Equations (1), (2), and (3). Each player aims to maximize its payoff by choosing the appropriate values of x_j or y_j. The players achieve the equilibrium state if the following conditions hold: $\overline{\mu(\Omega_j)} = \max_X \sum_{j=1}^{n} x_j * M_j$,

$$\overline{\mu(\Omega_{-j})} = \max_Y \sum_{j=1}^{m} y_j * M_{-j}.$$

The *BNE* of a game is comprised of the strategies for both players, in the form of (x_j^*, Ω_j^*) and (y_j^*, Ω_{-j}^*), which satisfies inequality (4). Hence, the *BNE* solution is unique and it is given by

$$\overline{BNE} = \left[\overline{\mu(\Omega_j), \mu(\Omega_{-j})}\right]. \tag{7}$$

The ground station requests u_i to fly over the disconnected segment J_j with a direction H_j when the equilibrium is reached, ie, $\max_X \sum_{j=1}^{n} x_j * M_j$. This ensures a trade-off between a high accuracy prediction of disconnected segment Ψ_j (see Equation (8)) and low energy consumption generated by UAV u_i. In this case, u_i plays the role of relay node, ie, V2U communication, and therefore, the end-to-end delay and PDR will be decreased. The pseudocode of V2U communication is illustrated in Algorithm 1. □

Algorithm 1 V2U communication

Begin
  Ground station collects hello messages from vehicles by using V2Gr, I2Gr, or/and U2Gr
  if (There is a V2Gr | | I2Gr communications) | | $(E_i \geq E\max_i)$ **then**
    Ground station computes $\mu(\Omega_j)$;
    if $(\mu(\Omega_j) \geq \overline{\mu(\Omega_j)})$ **then** J_j is covered by for V2U communication;
  else if (There is a V2Gr | | I2Gr communications) | | $(E_{-i} \geq E\max_{-i})$ **then**
    Ground station computes $\mu(\Omega_{-j})$;
    if $(\mu(\Omega_{-j}) \geq \overline{\mu(\Omega_{-j})})$ **then** J_j is covered by u_i for V2U communication;
End

From Equation (8), we show that, when the ground stations predict all the disconnected segments, the PDR of network tends to zero, and hence, Ψ tends to infinity. In this game, we set $0 \leq \Psi \leq 1$.

$$\Psi = \frac{1}{\mathrm{PDR}_j} \tag{8}$$

4.2 | Broadcast storm mitigation technique

To mitigate the broadcast storm and decrease the overhead at UAV level, the number of vehicles that send *hello messages* to the UAV should be minimized, which may significantly affect the accuracy of the prediction algorithm. Therefore, for the ground station to achieve a high accuracy prediction of disconnected segments, a critical trade-off needs to be met between the number of active vehicles in providing enough information to the UAV. Note that, throughout the present work, we focus on reducing the effects that the broadcast storm has on UAVs in data gathering phase, ie, without the presence of LTE cellular network and V2Gr communication. As the communication aspect plays an important role in our approach, we first introduce the communication model for wireless access. Then, we give the details about the broadcast mitigation technique in the following sections.

4.2.1 | Communication model

The communication process could be either between vehicles (V2V), ie, local mode or between vehicle and UAV (V2U), ie, global mode. In this latter, the UAV assigns a time slot for each active neighboring vehicle.

In global mode, the UAV manages the uplink communication of vehicles that want to communicate with it. There are N vehicles that want to communicate with UAV, where a set of vehicles is denoted as $V = \{1, \ldots, N\}$. We denote α_n as the

global mode decision of vehicle n, $\alpha_n > 0$ if vehicle n decides to launch the global mode; otherwise, $\alpha_n = 0$. The data rate D_n of a vehicle in this mode, ie, $\alpha_n > 0$, is computed as in the works of Rappapor[27] and Chen et al[28] and is equal to

$$D_n = b * \log_2\left(1 + \frac{p_n * p'_{n,u}}{b_0 + \sum_{i=1}^{N} p_i * p'_{i,u}}\right), \tag{9}$$

where b and b_0 are respectively the bandwidth and noise power, p_n is vehicle n's transmission power and $p'_{n,u}$ is the channel gain between vehicle n and UAV u.

In our approach, we consider that each vehicle n has a communication task $\theta_n \triangleq (T_n, N_n)$ that can be either between vehicles or between vehicle and UAV. T_n denotes the size of message (in bits) involved in communication task θ_n and N_n is the number of messages that a vehicle n broadcasts. The UAV u_i would incur a certain overhead in terms of time and energy consumption for receiving the message from vehicle n. We can compute the transmission time (t) and energy consumption (e) of UAV u_i for receiving the message of size T_n as in the work of Chen et al.[28]

$$t_{u_i} = \frac{T_n}{D_n} \tag{10}$$

$$e_{u_i} = \frac{N_n * T_{n*p_n}}{D_n} \tag{11}$$

From Equations (10) and (11), we define the overhead at UAV u_i based on the transmission time (t) and the energy consumption:

$$O_{u_i} = \alpha t_{u_i} + \beta e_{u_i}, \tag{12}$$

where α and β denote the weighting parameters of transmission time and energy consumption for UAV u_i, respectively, when vehicle n decides to activate its global communication mode.

Many vehicles could simultaneously send their hello messages to UAV u_i; this would incur a high overhead and cause the UAV to consume high energy in processing these hello messages. In addition, severe interference could occur, which leads to a decrease in data rate.[28,29] To address these issues, only an optimal number of vehicles activate their global communication. However, these vehicles must ensure to provide enough information, ie, hello messages to the UAV in order to allow the ground station to predict the disconnected segment with a high accuracy (in case where there is no LTE coverage or V2Gr communication mean). This dilemma between a low overhead and a high accuracy prediction is addressed by using the game theory as explained in the following.

4.2.2 | Communication game

We model the vehicles that want to communicate with UAV u_i as players in order to optimize the slot assignment using game theory approach. In other words, to make a trade-off between high accuracy predictions of a disconnected segmentΨ, ie, number of vehicles that communicates the hello messages to UAV u_i and low overhead O_{u_i}. The game is modeled as $J(N, S, G)$, where N is the number vehicles players that want to communicate with UAV u_i, S are their strategies, and G are their gain functions.

G_j is the gain function of vehicles v_j, which is the overhead generated by the UAV when v_j sends hello message of size T_n that can be formulated by Equation (12).

The gain total of UAV-assisted vehicles nodes can be formulated as shown in Equation (13)

$$G_{\text{total}} = \sum\nolimits_{j \in \{1, \ldots, N\}} O_{u_i j}. \tag{13}$$

s_i is the strategic decision-making performed by the player v_j, which could be either a local or global decision (these two modes are defined in Section 3). The strategies of v_j, s_i can be defined as follows:

$S_j = \{s_i; \forall\, i \in (1 \triangleq \text{Local mode}, 2 \triangleq \text{Global mode})\}$.

We define v_{-j} as other players excluding player j and s_{-i} as their related strategies.

The goal of our game is to determine a consensus between players (v_j, v_{-j}) in order to converge to a steady state solution defined as Nash equilibrium (NE), which is a stability state of the game.[30,31] This stability is defined as the optimal number of players v_j that should active their global communication mode in order to deliver enough information to UAV u_i, ie, u_i assigns to each selected player v_j a time slot to communicate with, taking into account the resource constraints of the UAV (to minimize the overhead). To prove that our communication game converges to NE, we first should prove that this game is a potential game[32] since this latter has a property to admit always a NE solution.

Lemma 2. *J (N, S, G) is a potential game.*

Proof. According to the works of Chen et al[28] and Monderer and Shapley,[32] a game is a potential game if it admits a potential function Φ (s), defined as follows:

$$\Phi\left(s_i, s_{-i}\right) - \Phi\ \left(s'_i, s'_{-i}\right) = G_j\left(s_i, s_{-i}\right) - G_j\left(s'_i, s'_{-i}\right), \tag{14}$$

where i, s, and s' are any player v_j and any two strategies in the game, respectively. $J(N, S, G)$ is a potential game since Equation (14) satisfies the definition of potential function, where

$$\Phi\ \left(s_i, s_{-i}\right) = \mathrm{Min} G_{\mathrm{total}}\left(\Theta\right);$$

Here, Θ is Cartesian product of the players' strategies, ie, $\Theta = S_1 \times S_2 \times \cdots \times S_N$.

From Lemma 2, we can conclude that the potential game $J(N, S, G)$ admits a NE solution, ie, there is a consensus between players (v_j, v_{-j}) to deliver enough information to UAV u_i for better accuracy predictions of disconnected segment Ψ while minimizing the overhead Φ (s_i-s_{-i}). □

We divide the time into a set of time slots; at each time slot, the player v_j chooses its strategy according to the following equation:

$$s_i^{t+k} = \begin{cases} s_i^{t+1} \triangleq \text{Global mode}, & \text{if } \left(s_i^{t+1} {G_{\mathrm{total}}}^{t+1}\right) < \left(s_i^{t}, {G_{\mathrm{total}}}^{t}\right) \\ \text{and } \left(s_i^{t+1}, \Psi^{t+1}\right) > \left(s_i^{t}, \Psi^{t}\right) & \\ s_i^{t} \triangleq \text{Local mode, otherwise,} & \end{cases} \tag{15}$$

where $K = \{1, \ldots, M\}$ and M is the number of time slots.

The player keeps the strategy s_i^{t+1} if it results in a better overhead and accuracy prediction than that of the previous strategy s_i^t that it had in its previous turn and vice versa. It is noted that, in this game, we assume that the player has knowledge of overhead G_{total} generated by UAV u_i and the predicted disconnected segment Ψ since u_i exchanges with vehicles located within its radio range the information of Ψ and G_{total}. The optimal response of player v_j for choosing the strategy $s_i^t \triangleq$ Global mode is modeled as shown in Equation (16).

$$\begin{cases} \left(s_i^t, \arg \min_{G_{\mathrm{total}}} {G_{\mathrm{total}}}^t\right) \\ \text{and} \\ \left(s_i^t, \arg \max_{\Psi} \Psi^t\right) \end{cases} \tag{16}$$

The pseudocode of the global mode's activation without the presence of LTE cellular network and V2Gr communication is illustrated in Algorithm 2.

Algorithm 2 Communication modes

Begin
  UAVu_i computes G_{total} and Ψ
  $u_i$sends the couple (G_{total}, Ψ) to v_j and v_{-j}
  if $({G_{\mathrm{total}}}^t < {G_{\mathrm{total}}}^{t-1}$ & $\Psi^t > \Psi^{t-1})$ **then**
    Vehicle v_j activates its Global communication mode at time t
  else
    v_j activates its Local communication mode
    J_j is covered by u_i for V2U communication.
End

5 | EXPERIMENTAL RESULTS

In this section, we present the results of our proposed UAV-aided VANET framework (UVE). Our solution was implemented in Network Simulator 3.[33] A series of tests have been carried out and are presented. We conducted the

TABLE 2 Simulation parameters

Simulation Area		$20\,000 \times 20\,000$ (m^2)
Simulation time		380 (seconds)
UAV's mobility model		Mobility model with energy constraint[12]
Vehicles number		From 50 to 350
802.11p transmission range		350 (meters)
UAV transmission range		450 (meters)
Vehicles velocity	Min	90 (km/h)
	Max	150 (km/h)
	Step	18 (seconds)
UAV velocity	Min	60 (km/h)
	Max	110 (km/h)
	Step	15 (seconds)
Routing protocol		Cluster-based protocol[37]
Mobility generator		SUMO[34]
Number of intersections		40 segments
Number of traffic lights		25
Propagation model		Log distance
Map		Map of Eichstätt from OpenStreetMap

Abbreviations: UAV, Unmanned Aerial Vehicle; SUMO, Simulation of Urban Mobility.

on-the-ground simulation in the Manhattan area using the Simulation of Urban Mobility (SUMO) simulator.[34] Two different topologies were implemented: two parallel highways (2×3 lanes) and an urban scenario generated by SUMO. To simulate the mobility of a UAV, our deterministic mobility model[12] is used. In this model, the UAVs are required to achieve an optimal area coverage rate while maintaining connectivity with their neighboring UAVs and a ground base station.[35] While optimizing area coverage and maintaining network connectivity, this model considers also energy as decision criterion.

The energy consumption generated at each UAV is computed as follows:

$$E = E_C + E_M, \tag{17}$$

where E_C is the energy caused by the communication process and E_M is the energy generated during the movement of the UAV. Furthermore,

$$E_C = E_T + E_R, \tag{18}$$

where E_T and E_R are energy cost to transfer and receive M-bit, respectively.

Following the work of Li et al,[35] E_M is defined as follows:

$$E_M = \theta N \varpi, \tag{19}$$

where ϖ is the rotational speed of a propeller, θ is the torque required to drive a propeller, and N is the number of propellers. For more details on how to compute θ, N, and ϖ, we refer the reader to the work of Phung and Morin.[36]

The main simulation parameters are summarized in Table 2. These parameters were chosen to be as closely realistic as possible. We compare the performance of UVE with some infrastructure-assisted VANET, UVAR,[7] and ODEL.[2] The metrics used in our evaluation are defined as follows.

- **Packet delivery ratio:** the number of correctly delivered packets to the target destination over the total number of packets sent by the sender.[7,38,39]
- **End-to-end delay:** the average time that packets spend to reach destinations.[7,38]
- **Communication overhead:** the number of bytes generated by vehicles to achieve a better packet delivery ratio.[40]

The most important results are summarized as follows.

5.1 | Optimal number of nodes

In this section, we investigate the impact of the number of UAVs and vehicles that activate their global mode (ie, vehicle communicates its hello message to UAV) on packet delivery ratio, end-to-end delay, accuracy prediction of disconnected segments, and communication overhead, when LTE coverage and V2Gr communications are not available. Note that, in this investigation, the proposed prediction game and broadcast storm mitigation techniques are not activated.

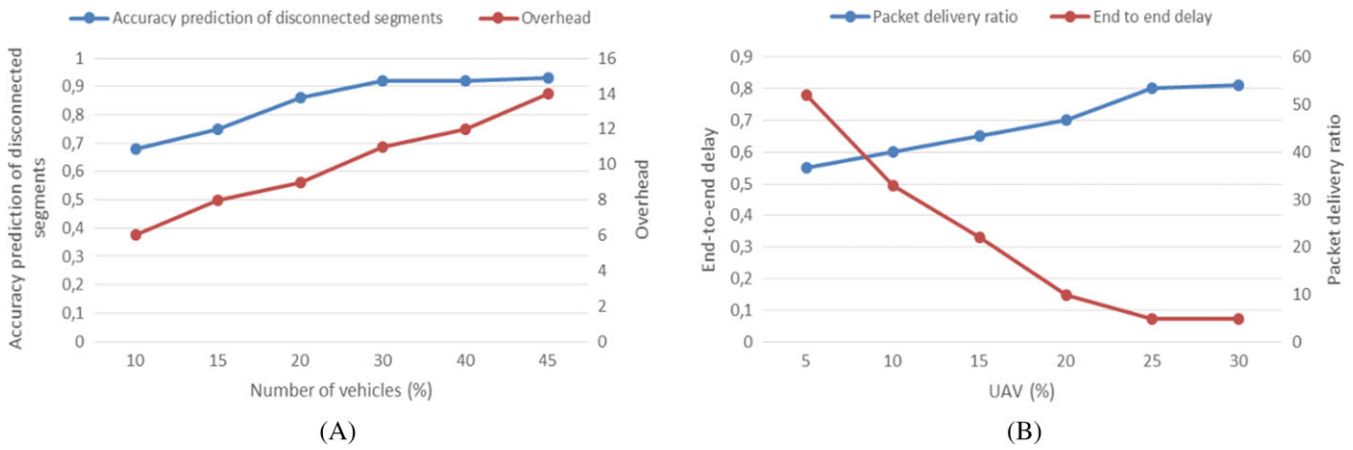


FIGURE 4 Optimal number of vehicles and Unmanned Aerial Vehicles (UAVs). A, Accuracy prediction vs overhead; B, Packet delivery ratio vs end-to-end delay

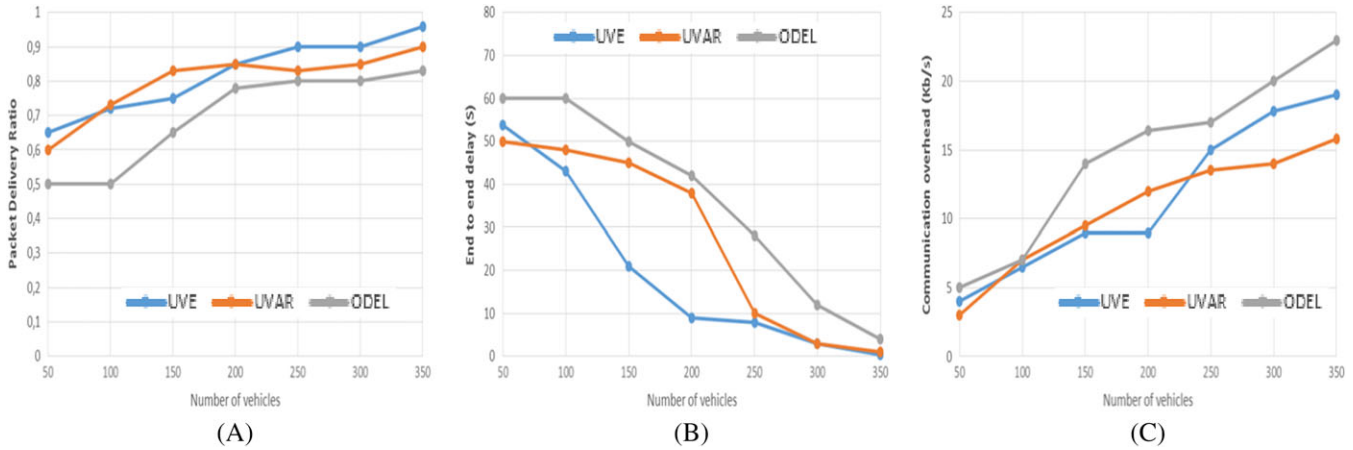


FIGURE 5 Global communication mode. A, Packet delivery ratio; B, End-to-end delay; C, Communication overhead

Figure 4A shows how many vehicles activating their *global mode* will influence the accuracy prediction of disconnected segments and communication overhead. When this number increases, both accuracy prediction and overhead tend to increase. Furthermore, when the number of these vehicles is equal to 30% of overall vehicles, the accuracy prediction remains almost constant. This is due to the fact that the equilibrium state (ie, trade-off between accuracy prediction and overheads) is reached when this number is equal to 30%.

In Figure 4B, we vary the number of UAVs that fly over disconnected segments, by fixing the number of vehicles (that activate their *global mode*) to 30% of overall vehicles. It is apparent that, when the number of UAVs rises, both packet delivery ratio and end-to-end delay increases and decreases, respectively. Furthermore, when the number of UAVs is equal to 25% of overall vehicles, these metrics remain almost constant. In addition, 25% is an optimal number, since the trade-off between the packet delivery ratio and end-to-end delay is achieved (ie, NE point) when this number is reached.

In conclusion, we claim that, when the numbers of UAVs and vehicles that activate their global mode are equal to 25% and 30% of overall vehicles, respectively, both packet delivery ratio and end-to-end delay will be enhanced, while the energy constraints of the UAVs are taken into account.

In the following, we analyze the performance of UVE with some infrastructure-assisted VANET, UVAR,[7] and ODEL[2] in terms of packet delivery ratio, end-to-end delay, and the communication overhead.

5.2 | Performance comparison

As shown in Figures 5, 6 , and 7, we vary the number of vehicles from 50 to 350 and compute the metrics cited above, where the following scenarios are considered.

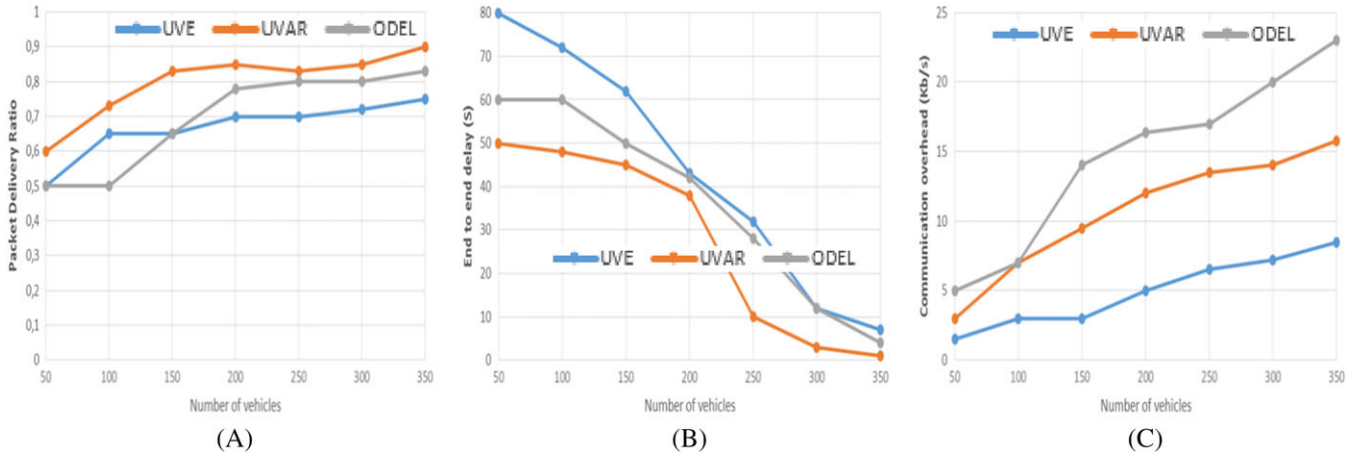


FIGURE 6 Local communication mode. A, Packet delivery ratio; B, End-to-end delay; C, Communication overhead

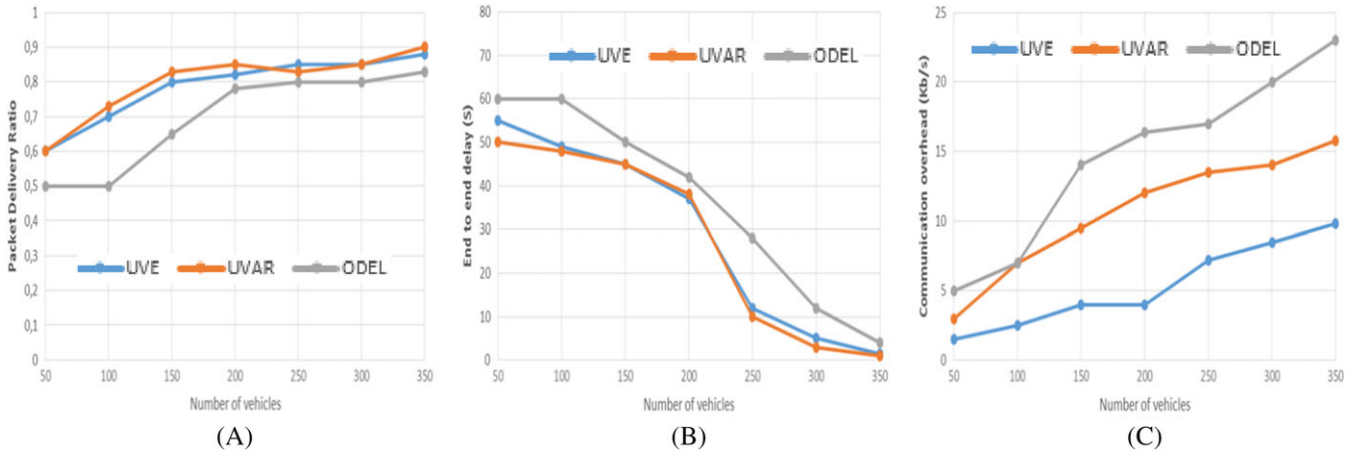


FIGURE 7 Global mode's activation—using the broadcast mitigation technique. A, Packet delivery ratio; B, End-to-end delay; C, Communication overhead

(i) The communication mode of all vehicles is local (ie, vehicle exchanges its hello message with another vehicle when they meet). Results are plotted in Figure 6. (ii) The communication mode of all vehicles is global. Results are plotted in Figure 5. (iii) The activation of global mode is done using our broadcast mitigation technique. Results are plotted in Figure 7. It is apparent that, to achieve a better packet delivery ratio and a low end-to-end delay, all vehicles should activate their global communication mode as shown in Figure 5; however, this might lead to a high communication overhead by vehicles. On the other hand, in order to get a low communication overhead, all vehicles should activate their local communication mode. However, both packet delivery ratio and end-to-end delay will be decreased and increased, respectively, specifically when the number of vehicles is high as shown in Figure 6.

From Figure 7, we can see that our broadcast mitigation technique has the ability to ensure a good trade-off between a high packet delivery ratio and a low end-to-end delay and to maintain a low communication overhead. This result is due to the fact that only an optimal number of vehicles are selected to deliver the hello messages to the UAVs; while the vehicles deliver enough information to allow UAVs to place themselves for allowing relaying of data when connectivity between vehicles is not available. By reducing the communication overhead, the UAVs' lifetime will be increased, and hence, the end-to-end delay and packet delivery ratio will be decreased. In this study, we are interested to investigate the performance of a vehicular network in an extreme environment, ie, with no LTE coverage and V2Gr communication.

In Figures 7A, 7B, and 7C, we distinguish between the performance of UVE and UVAR in terms of packet delivery ratio and end-to-end delay as compared to ODEL. This latter uses a static relay node (RSU) to help data forwarding, which is not suitable for a network with high mobility nodes and frequent network disconnections. In addition, in Figure 7C, we can see that the highest performance in terms of communication overhead is achieved by UVE even in scaling mode, ie, when the number of vehicles is high. The excellent performance of UVE is attributed to the following reasons.

- *Prediction game:* with a help of *NE* concept, we predict disconnected segments in which the drones fly over and hence play the role of relay nodes, ie, V2U communication. This concept ensures a trade-off between a high accuracy prediction of disconnected segments and low energy consumption generated by UAV.
- *Broadcast storm mitigation technique:* this technique is very useful for VANET in extreme environments, where the deployment of UAVs to execute the tasks of data gathering and relaying is required. As explained above, such techniques aim to reduce the number of vehicles that broadcast hello messages to UAVs, while ensuring a better accuracy prediction of disconnected segments.

6 | CONCLUSION

In the present paper, we have proposed a new framework that uses small UAVs as mobile infrastructure nodes to enhance the connectivity between the mobile vehicles. For this purpose, two major techniques have been presented: (i) prediction of disconnected segments and (ii) broadcast storm mitigation. In the first one, we have used a prediction game based on the concept of *NE*, to predict the occurrence of disconnected segments so that a drone can be sent to handle disconnections. The dilemma between high accuracy prediction probability and low energy consumption for the deployed UAVs is ensured. For the second part (ie, the broadcast storm mitigation), we have developed a technique that consists of controlling the number of vehicles that broadcast hello messages to the UAVs while still ensuring a high accuracy prediction of disconnected segments. Such a method is very useful for vehicular networks, particularly in infrastructure-poor environments (ie, no LTE coverage and 802.11p communication), where an efficient usage of UAVs for data gathering and relaying of tasks is required. Our simulation results have shown that UVE requires only a low overhead to ensure a low end-to-end delay and high packet delivery ratio as compared to the current infrastructure-assisted VANET proposed in the works of Mehar et al[2] and Oubbati et al.[7] Since the number of vehicles is above 300 nodes, the packet delivery ratio and end-to-end delay are close to 0.9 and 0.4 seconds, respectively, while the communication overhead is less than 10 kB/s.

As future research work, our main goal is to propose an efficient UVE for highly scalable vehicular networks, by developing a robust channel characterization model while maintaining an efficient energy mobility model of the UAVs.

The security in UAV-assisted vehicular network is mandatory due to the lethal attacks that are launched by the hackers against this heterogeneous network. Therefore, as future work, we aim to integrate the proposed cybersecurity framework[9] in such kind of heterogeneous network.

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