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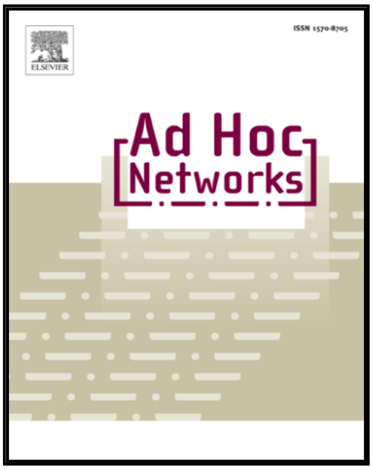

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UAV Mobility Model for Dynamic UAV-to-Car Communications in 3D Environments

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Abstract

In scenarios where there is a lack of reliable infrastructures to support car-to-car communications, Unmanned Aerial Vehicles (UAVs) can be deployed as mobile infrastructures. However, the UAVs should be deployed at adequate location and heights to maintain the coverage throughout time as the irregularities of the terrain may have a significant impact on the radio signals sent to distribute information. So, flight altitude and location should be constantly adjusted in order to avoid hilly or mountainous terrains that might hinder the Line-of-Sight (LOS). In this paper, we propose a three-dimensional mobility model to define the movement of the UAV so as to maintain good coverage levels in terms of communications with moving ground vehicles by taking into account the elevation information of the Earth's surface and the signal power towards the different vehicles. The results showed that our proposed model is able to extend the times with connectivity between the UAV and the cars compared to a simpler two-dimensional model, which never considers the altitude, and a static model, which maintains the same UAV position from the beginning to the end of the experiment.

Keywords: UAV; Simulation; Mobility; Vehicular Communications.

1. Introduction

Due to their flexibility in terms of deployment to create a networked environment, UAVs can be used as instant communication relays, especially in the

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case of emergencies. Since UAVs can fly at high altitudes, they can have a better LOS than communication nodes on the ground, such as fixed infrastructures [1]. This flexibility, in turn, allows the UAVs to offer more advantages as data relays and, thanks to their mobile capabilities, UAVs can be deployed as mobile infrastructure elements to provide service to vehicles. In the scope of Intelligent Transport Systems (ITS), some of the use cases where UAVs can be deployed include remote sensing [2] and disaster assistance operations [3], among others.

Within the vehicular communication scenarios, there can be some cases where direct multi-hop car-to-car communications are not reliable at ground level. To tackle this problem, a possible solution is to deploy the UAVs to forward the information related to car-to-car communications, acting as information relays [4]. Thanks to the flexible movements in the three-dimensional space, UAVs can follow certain trajectories or routes with complete freedom, which contrasts with vehicles on the ground, which typically have to move within road boundaries. Having the ability to explore space while respecting maximum altitude values, a UAV may move freely and avoid obstacles that can cause Non Line-of-Sight (NLOS) conditions, e.g. mountains, high buildings, etc [5]. Compared to the fixed infrastructures on the ground that support car-to-car communications, UAVs are mobile. Hence, UAVs can work as mobile Road Side Units (RSUs) [6].

By making use of their freedom to explore the three-dimensional space, UAVs can adjust their position dynamically if they want to offer the best signal coverage to ground vehicles. In order to determine their path or trajectory, UAVs can make use of different mobility models, which can be tested either in real testbeds or simulation [7]. There are mobility models intended specifically for UAVs which are mostly mission-based mobility patterns [8]. However, if we aim at using UAVs to relay information from the moving nodes on the ground, the movement should be determined by taking into account the dynamic position of ground nodes.

This paper extends the results of our previous work presented in [9], where we propose a mobility model specifically for UAV movements to provide reliable communications to ground vehicles in the scope of car-to-car communications by relaying information from one car to another. Compared to the previous work, which only considers the mobility in two-dimensional space, this work focuses more on how the mobility of the UAV conforms to the altitude. In other words, the UAV's position should change depending on the altitude.

The movement of the UAV must aim at maintaining the connection between the cars on the ground throughout time, as depicted in Figure 1, illustrating the car connectivity assisted by a UAV in an area that has irregular terrains. Hence, the UAVs' movement is determined by their next position, which depends on the position of the cars on the ground, which in turn is also varying throughout time. In this case, the parameter to optimize is the signal power on each of the links between the UAV and the different ground vehicles. This is related to the quality of the signal received by the cars when the UAV is acting as a transmitter. The quality of the signal is thus defined by a path loss model developed in our previous work [10]. The aforementioned model is determined by the eleva-

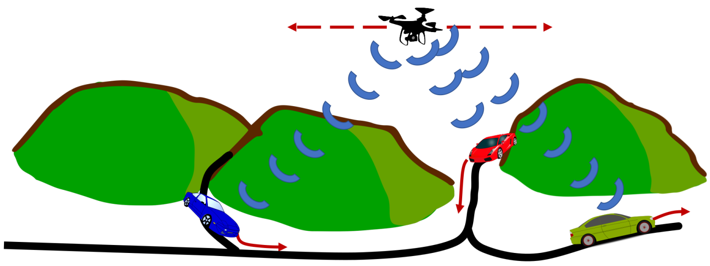


Figure 1: UAV Supporting Car Connectivity in a Hilly Area.

tion condition or height of the terrain in three-dimensional environments, where communication obstacles can derive from terrains having higher elevation compared to the position of transmitter and receiver. Hence, the proposed mobility model also accounts for the flight height of the drone. This way, the UAV has to move according to adequate heights to avoid crashing and, more important, by making sure the link towards each car remains stable, and not blocked by hills or mountains. Extending the previous work with the same scenario, the proposed model can determine the mobility of the UAV by not only adjusting its position relative to the real position of the cars on the ground in terms of latitude and longitude but also finding its ideal position in terms of height by making use of its greater freedom to explore the three-dimension space.

The remainder of this paper is organized by first presenting some related research works in Section 2. Our proposed mobility model that is impacted by the path loss model, will be discussed in Section 3, along with the problem formulation. The implementation of the mobility model in simulation will be explained in Section 4, along with how the scenario is defined and how to set up the simulation. The results of the simulation will be presented and discussed in Section 5. Finally, the paper's conclusion and future works will be presented in Section 6.

2. Related Works

Several research efforts have been conducted by linking UAVs and cars in simulation, such as the work by Sliwa et al. [11], where the researchers proposed a simulation framework for aerial and ground-based vehicular communication networks. The work by Jia et al. [12] investigates the case where UAVs are deployed as flying base stations to improve connectivity to the cars in areas affected with disaster. Vehicle-to-drone communications were also studied in terms of delay by Seliem et al. [13]. In an effort of combining the UAVs and cars in a networked environment, Shilin et al. [14], conducted a study on how the UAVs can act as information relays for disconnected groups of cars.

Related to UAV-to-car communication simulations, we have previously worked on the optimal placement of the UAV to support car-to-car communications

[15, 16]. The placement method aims to find the best position of the UAV that can maintain the connectivity towards the cars on the ground using optimization algorithms. The placement technique attempts to dynamically find the best position of the UAV at every second accounting for the movements of the cars on the ground. However, the approach remains theoretical, and cannot be used as the basis for a UAV mobility model since it has to have full knowledge of the area before deployment. Hence, it cannot be used in any type of unknown environments.

In order to determine the movement of a node that experiences both location and velocity changes, a mobility model is proposed in [17]. For instance, the random mobility model can be used for determining the movement of a UAV by randomly exploring the area, e.g. Random Waypoint Mobility (RWM) model [18]. The movement can also be defined based on time, through the time-dependent mobility model in which the movement is defined by the previous speed and direction. An example is the Gauss-Markov mobility model [19]. Another movement pattern relies on predefining the selected path scheme. In this case, the UAV's mobility is planned beforehand. An example that follows this approach is the Paparazzi Mobility Model [20], in which the node using this model travels according to a specific pattern.

Besides the general mobility models for ad-hoc networks, several research efforts have been conducted to propose mobility models specifically for UAVs. Kuiper et al. [21] proposed a UAV model for reconnaissance scenarios. Wang et al. [22], proposed a model that considered the UAV movement based on a semi-random circular movement, which is an enhanced model compared to the Random Waypoint. The work by Sanchez-Garcia et al. [23] emphasizes on the mobility model for UAVs in disaster scenarios. With the proposed model, UAVs can offer maximum coverage to the people on the ground while still maintaining the connectivity with other UAVs at the air.

In contrast to general mobility models mentioned, which mostly focus on 2D movements, the mobility models used for UAVs can also target the three-dimensional space. One of the existing mobility models is the 3D Gauss-Markov Mobility model [24], where the authors modified the Gauss-Markov mobility model so as to explore the 3D space. Other works include the improved 3D Gauss-Markov model for dynamic and uncertain environments [25], namely 3D-DUMM. On the other hand, the author in [26] improved the random mobility model specifically for three-dimensional scenarios, where the model depends on the z axis direction (vertical movement).

Something missing from the existing works presented above is a mobility model that specifically addresses the UAV movement to support car-to-car communications in a three-dimensional environment. Hence, our contribution in this paper is how to determine the best mobility pattern for a UAV so as to dynamically find the best position to support UAV-to-car communications. The position should optimally conform the best link towards the cars on the ground that remain moving at all times. Hence, the UAV mobility pattern should be constantly and timely adjusted with respect to the mobility of the cars on the ground. Our mobility model considers the three-dimensional space, meaning that the mobility will not only define the movement to variations in terms of latitude and longitude but also vertically in terms of altitude. The performance of the mobility model is assessed using a realistic path loss model, which considers the signal propagation effects in the presence of irregular terrains.

3. Optimum UAV Mobility

3.1. Problem Formulation

Our proposed mobility model is intended for a case study in which a rural area has irregular terrains that makes up mountains and hills. Hence, the roads can have different elevation levels. This, in turn, causes the links between the cars on the ground to suffer from NLOS conditions. Also, one of our assumptions is that infrastructures are quite limited since the location is quite remote. Hence, car-to-car communications cannot be supported by any existing information relay in the area.

In our proposal, cars can communicate with a UAV acting as a mobile relay to enhance connectivity between them. The UAV can forward the information from one car to another, working as mobile infrastructure. The cars are following specific routes, and hence the UAV should adapt its position by considering the mobility of the cars along their routes.

In order to adapt its position, the UAV has to take into account the signal quality received by the cars on the ground. The UAV should be moving towards a new position where it can still offer adequate signal levels towards the cars at the time the cars are moving. The signal quality is calculated with respect to NLOS conditions from the transmitter to the receiver caused by the irregular terrains, such as hills or mountains, that can hinder the transmitted signal from the UAV to the cars. Hence, to adapt its position (as the environment is three-dimensional), the UAV should care about the height when flying, and also account for the elevation level associated with ground vehicle positions.

To calculate the value of the Received Signal Strength Indicator (RSSI), which is the main parameter affecting the mobility model, we use a specific path loss model. The path loss model is based on our previous work [10]. In particular, the RSSI is obtained by calculating the transmitted signal that is affected by the terrain height that might be the obstacles. The height of the terrain is determined by the elevation information retrieved from the Digital Elevation Model (DEM) [27]. With the DEM, it can be determined whether the terrain is high enough so as to become an obstacle to the transmitted signal. If that is the case, then there is an NLOS condition between the nodes. The obstacle that creates an NLOS condition is treated as knife-edge, as shown in Figure 2. The loss is calculated as multiple knife-edge diffraction that is included as a factor in the Bullington model [28], which is the base of our path loss model.

In order to calculate the height of the knife, the position of the UAV and the position of the cars towards the elevation level of the terrain should be taken into account. A knife is spotted when the LOS line between the sender and the receiver is lower than the elevation of the terrain. The signal attenuation is obtained by defining the diffraction from the Fresnel-Kirchoff diffraction [29], which is included in the developed model we have mentioned above.

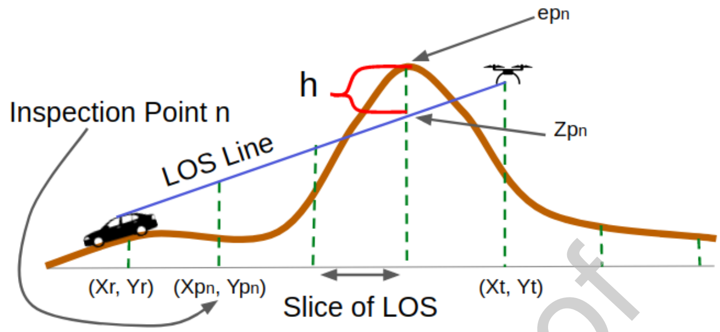


Figure 2: Detecting hills as obstacles to communication [10]

3.2. Proposed Mobility Model

The proposed mobility model is mostly based on following the ground nodes. The UAV will be attracted by the node, i.e., car in this case, from which it receives the weakest RSSI. The main goal is to maintain the connectivity from the UAV towards the cars on the ground so as to guarantee successful delivery of packets. Hence, when the UAV realizes that the RSSI towards a specific car must be improved, it starts moving towards it.

Our proposed mobility model can be represented by Algorithm 1. Firstly, the RSSI received by each car $(RSSI_1, RSSI_2, RSSI_3, ..RSSI_n)$ must be obtained. Following that, those values that belong to each specific cars, are compared with each other. The lowest value should be pointed out, along with the car which is associated with it $(RSSI_m in)$. Once that car has been identified, its location should be retrieved (Pos_{min}). With this information, the UAV movement is determined, and it uses the current location of the car as the target direction. The new position is changed into Pos_{i+1}, determined as $(Lat_{i+1}, Lon_{i+1}, Alt_{i+1})$. A new calculation is made after one second. At this point, the UAV will recalculate whether it should continue moving towards the same car, or switch to another car experiencing a lower RSSI value. For the implementation of the model, the Lat and Lon coordinates, in this case, should be translated from Global Positioning System (GPS) coordinates, which uses degrees, into scenario Coordinates, which use meters. This way, the Lat, Lon, and Alt values can have the same measurement unit.

4. Simulation Setup and Scenario

4.1. Implementation of the Mobility Model in Simulation

In order to test the mobility model in simulation, we have extended the existing simulation tools by developing a new extension module. The simulation

Algorithm 1 3D Mobility Model Algorithm

Input:
Initial UAV Position, Pos_i (Lat_i, Lon_i, Alt_i),
Speed of the UAV ($speed$),
Simulation Update Interval ($updateInterval$),
RSSI of cars ($RSSI_1, RSSI_2, RSSI_3, ..RSSI_n$).

Output:
Position of the Car with the lowest RSSI (Pos_{min}).
Next UAV Position (Lat_{i+1}, Lon_{i+1}, Alt_{i+1}).

$RSSI_{min} = min(RSSI_1, RSSI_2, RSSI_3, ..RSSI_n)$
$Pos_{min} = (Lat_{min}, Lon_{min}, Alt_{min})$
$dist_i = \sqrt{(((Lat_{min} - Lat_i)^2) + ((Lat_{min} - Lat_i)^2) + ((Lat_{min} - Lat_i)^2))}$
$RatioTraveled = updateInterval/(dist_i/speed)$
$Lat_{i+1} = Lat_i \cdot (1 - RatioTraveled) + Lat_{min} \cdot RatioTraveled$
$Lon_{i+1} = Lon_i \cdot (1 - RatioTraveled) + Lon_{min} \cdot PercentageTraveled$
$Alt_{i+1} = Alt_i \cdot (1 - RatioTraveled) + Alt_{min} \cdot RatioTraveled$

tools used in our work are the following: OMNeT++[30], which is a network simulator; SUMO [31] for simulating the movements of cars; and Veins [32], used to simulate a more realistic vehicular communications environment. The UAV mobility is determined by the RSSI. In this case, the UAV would move towards the car that is receiving the lowest RSSI value. To obtain this RSSI value, we have to execute all simulation tools combined, whether it be the network simulator and the traffic simulator, along with the vehicular network simulation framework.

Although the cars' movements are determined by the SUMO tool and impact the UAV's mobility, the UAV movement is, on the other hand, directly computed in OMNeT++. The RSSI or the signal strength is affected by the elevation obtained from the DEM. This is due to the fact that the signal transmitted must take into account the presence of hills in addition to the altitude of the transmitter and the receiver. The simulator can then determine if there is a signal blockage that can cause a knife-edge effect. The knife-edge effect can be spotted by calculating from the path loss model, according to [10]. This will in turn determine the signal strength, or the RSSI as depicted in Figure 3.

4.2. Simulation Setup and Scenario

A scenario is defined for the simulation in order to test the proposed mobility model. In this scenario, the location chosen was *Pont de Suert, Spain*. The location is adequate for our evaluation since it is a rural area with lots of hills, hence becoming an ideal place to test our model by introducing NLOS conditions due to the irregular terrain levels in that area. In order to have a more realistic simulation scenario, we have imported the map from Open Street Map (OSM) [33]. The actual layout of the roads is outlined in this map. In addition, we

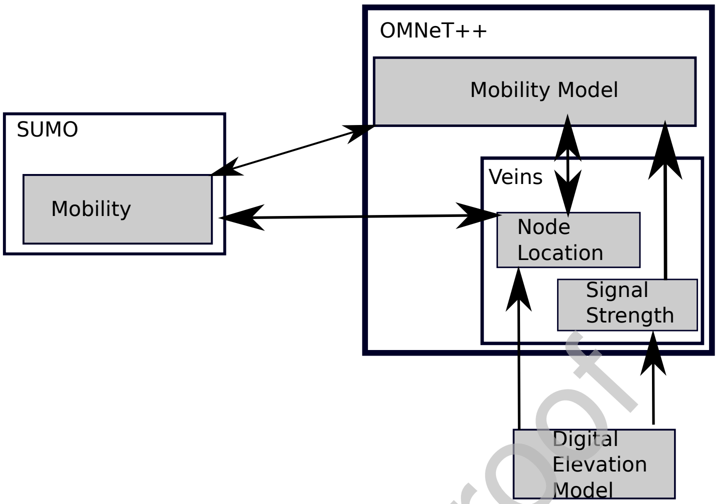


Figure 3: Mobility Model Configuration in Veins [9].

Table 1: Simulation parameters.

Parameter	Value
Transmission Power	200 mW
Antenna	5 dBi
Packet Size	1.4 kB
Message Type	Basic Safety Messages (BSM)
MAx. UAV Speed	72 km/h
Packet Transmission Rate	10 Hz

also imported the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM) [27] to add information about the terrain heights.

In order to achieve compatibility with OMNeT++, the map imported from OSM that contains the information in GPS coordinates is translated into Cartesian coordinates, having an area of 5000×5000 meters. Three cars are deployed in the scenario, in which each has its predefined route crossing each other at some point, as we can see in Figure 4. The scenario is centered at the intersection of three roads where the cars are located. The location of each car is recorded throughout time as the cars are moving. These locations are used to determine the mobility model, so that it gets the maximum coverage while maintaining the connectivity towards the cars on the ground in this scenario. The cars' movements are generated by the SUMO traffic simulator. The scenario is limited to a duration of 280 seconds, since the cars reach the boundaries of the downloaded map at the end of the simulation time.

In the simulation, the UAV generates User Datagram Protocol (UDP) packets that are transmitted in a broadcast manner as BSM) at a rate of 10 packets

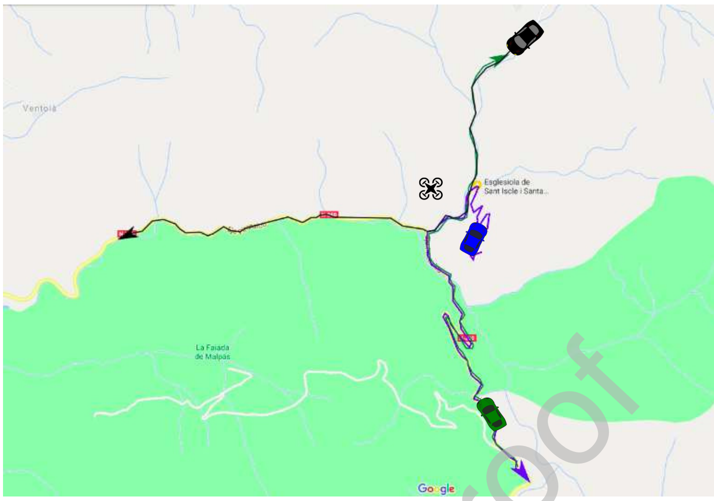


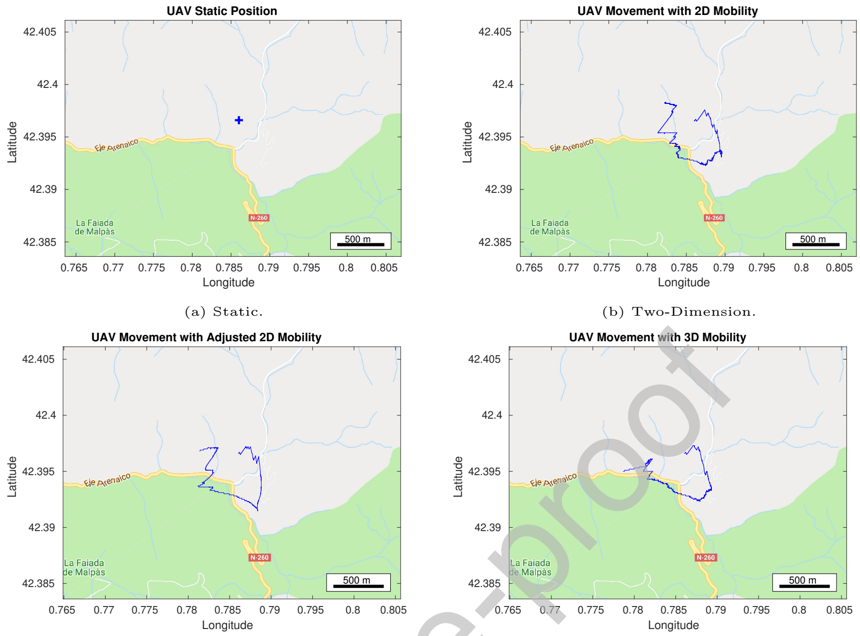
Figure 4: Trajectories for ground vehicles in our experiments [9].

per second. The communication between the cars and the UAV are in ad-hoc mode using the IEEE 802.11p technology. In more detail, the parameters considered for simulation are listed in Table 1.

To evaluate the performance of our model, and to prove that it offers a better mobility pattern, we have compared the three-dimensional mobility model with other three models. The models to be compared include the *static model*, where the UAV never leaves its initial position. The second model is the *2D model*. In this mobility model, the UAV moves around the space, but it never moves vertically (with no altitude changes). Finally, the third model is the *adjusted 2D model*. This model varies its altitude according to terrain features, but never varies its flight height, always maintaining a same distance towards the ground, which in this case is 78 meters in altitude for the whole simulation[1].

5. Simulation results

By conducting the simulations, it can be determined the best mobility pattern for the UAV with respect to the movement of the cars on the ground. The UAV's location can be traced through its trajectory in terms of latitude, longitude, as well as its altitude at every second. The receiver's average RSSI values obtained will determine the location of the UAV where it achieves the best coverage.



(a) Static.

(b) Two-Dimension.

(c) Adjusted Two-Dimension.

(d) Three-Dimension.

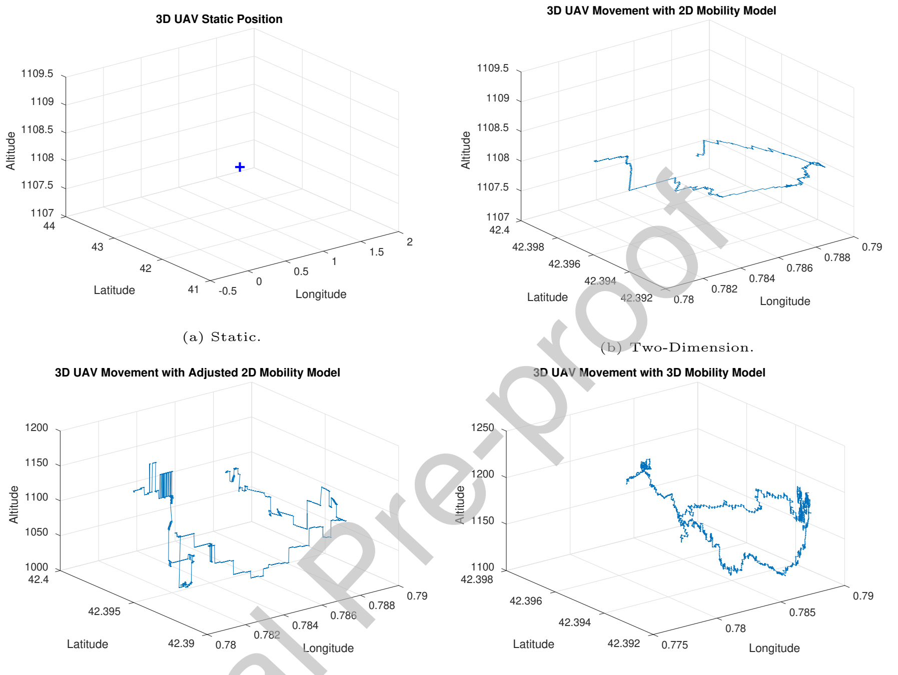
Figure 5: UAV Mobility in a 2D Map.

5.1. UAV Path Trajectory

The path trajectory of the UAV along the simulation time can be obtained from the GPS locations determined by each mobility model. The simulation is conducted using a real map from OSM, allowing us to have the path projected on the map, as depicted in Figure 5. Each figure represents the position of the UAV throughout the simulation for each mobility model: static model, 2D model, adjusted 2D model, and our 3D model. For the static model, the UAV remains still from the starting time until the end of the simulation, located at a strategic position near the center of the cars' locations, as depicted in Figure 5a. As for Figure 5b, it is based on the mobility trace from the 2D mobility model. Notice how the UAV moves towards the north, which is the location of the car that has the lowest signal quality received at the beginning, then going to the south, towards the location where the other car was located, and finally going west. A similar pattern is shown when using the adjusted 2D mobility model, as shown in Figure 5c. By using this model, the trend is similar, but the only difference is that the UAV approaches the car by calculating the distance in 3D, even though it maintains its flight height. The results with the 3D model are

[1]Please keep in mind that altitudes of more than 400 feet above ground are typically not allowed (legal requirement).

shown in Figure 5d; we can see a slight difference as it varies the flight height, thus having a pattern that is not similar to the previous two. In particular, the UAV moved in the 3D space by approaching the car having the lowest signal taking into account the elevation height towards the ground.



(a) Static.

(b) Two-Dimension.

(c) Adjusted Two-Dimension.

(d) Three-Dimension.

Figure 6: UAV Mobility in 3D Space.

To have a better view of the results, we have also built a representation of the UAV movement in a three-dimensional space. The UAV paths using the different models are presented in Figure 6. In these figures, we have presented the trace of the UAV with the altitude information. For the static model, as shown in Figure 6a, the UAV not only maintains its position in terms of latitude and longitude, but it stays still in terms of altitude. When using the 2D model, however, it moves around varying its position in terms of latitude and longitude, although its altitude never changes. We can see the difference when we use the adjusted 2D model. In this case, the altitude changes to adapt to the terrain topology, even though, in terms of latitude and longitude, it has the same pattern as the 2D model. A considerable change can be seen when using the 3D model. In the latter, changes in terms of altitude are somehow not as rigid as the adjusted model. While in the adjusted 2D model the UAV moves either horizontally or vertically, the 3D model allows the UAV to move diagonally when attempting to approach the car experiencing lower signal levels, and also to freely adjust its altitude towards the ground.

5.2. Impact on Received Signal Strength

To measure the performance of the proposed mobility model and its effectiveness, we have chosen the RSSI as the key performance indicator. The RSSI is measured according to the simulation time. The four tested models in our work have been compared, and the values are plotted in Figure 7. The worst results are obtained with the 2D model. In this model, the altitude of the cars on the ground are not taken into account, which results in selecting worse position adjustments. In particular, near the end of the simulation time, the results produced by the 2D mobility model are much worse than for the remaining models. On the other hand, the best result is achieved by the adjusted 2D mobility. As we can see in the figure, in the time range between t = 50s and t = 180s, the average RSSI perceived by the cars has been above -85 dBm, although from t = 180s onwards the 3D mobility model performs the best.

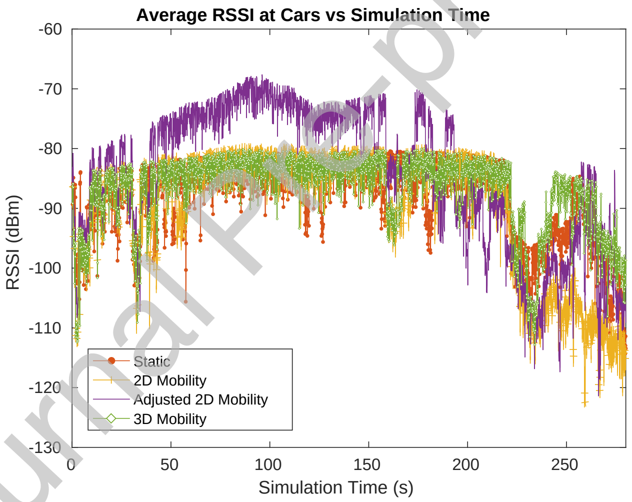


Figure 7: RSSI vs Time.

Moreover, we can analyze the results from another perspective by presenting the data distribution using box plots, as depicted in Figure 8. Results for the 3D mobility model are clearly the best and the most stable, being that the majority of the values are above -89 dBm (the threshold for successful packet delivery). On the other hand, the adjusted 2D mobility model provides 75% of the results with a larger range, with most of the values up to -74 dBm, performing worse than the static option. However, although during some periods the adjusted 2D mobility model may offer the best signal levels, it cannot maintain good coverage on the long term, which will be further confirmed in the next subsection.

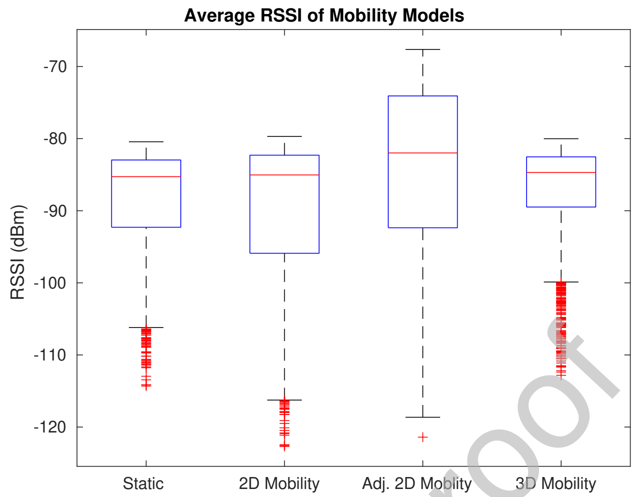


Figure 8: RSRSSI Obtained from Different Models.

5.3. Impact on Flight Height and Altitude

When considering how high the UAV has flown, we gathered the information plotted in Figure 9 and Figure 10. If we consider the altitude of the nodes in the simulation, as depicted in Figure 9, we have plotted the nodes' altitude versus simulation time. In this figure, we have compared the UAV altitude when using the four different models, and the altitude of the three cars on the ground. Here the altitude of the UAV, when it is static or adopting 2D mobility, was maintained throughout the entire simulation process. However, the case with adjusted 2D mobility and 3D mobility have variations. In the case of 3D mobility, the altitude varies and somehow has a higher altitude when compared to he adjusted 2D mobility. This shows that the 3D mobility model has indeed searched for the best flight height in a way that it can still reach the communication with the three cars on the ground. On the other hand, the adjusted 2D mobility model only varies the altitude because it must maintain its flight height with respect to the elevation of the terrain regardless of the altitude of the car on the ground.

A more detailed representation of how high the UAV has flown is depicted in Figure 10. In this case, we can see that the UAV models following the adjusted 2D mobility and the static one have maintained the flight height. We can also see that the 3D mobility model has changed altitude throughout time, as well as when using 2D mobility (which maintains its altitude, although varying its flying height). The UAV that flew according to the 3D mobility model has carefully taken care of how high it flies. This way, it is able to account for the distance towards the cars on the ground. As we know, if we apply the free space path loss theory, the further the transmitting node is located towards the

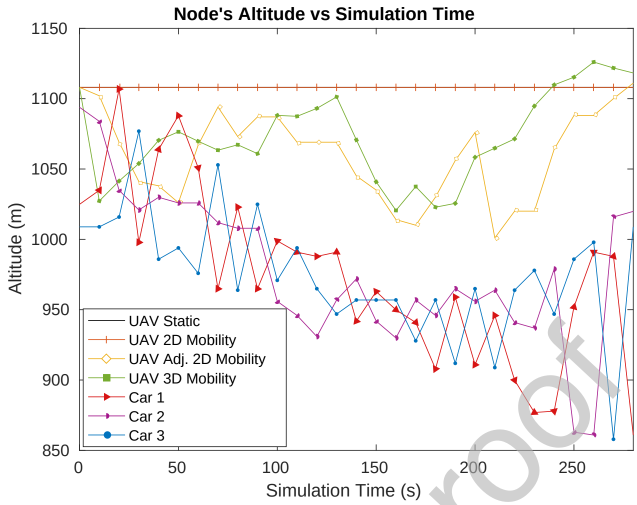


Figure 9: Altitude vs Time.

receiver, the lower the signal quality received. Here we can understand why, when using 2D mobility, the UAV transmitted signals are low in terms of RSSI when received by the cars.

5.4. Connected Time and Average RSSI in the Simulation

Another metric that allows us to assess how optimal is each model in terms of connectivity towards the cars on the ground is the duration of the coverage continuity throughout the simulation time. The period during which the UAV is connected to the cars is represented by the connected percentage time. Particularly, this metric shows a level of percentage towards the total simulation time, as defined in Table 2. The static model, which maintains the UAV position throughout the simulation time, maintains the connection active for 67.142 % of the evaluated time. If we use the 2D model, the connected time is of only 63.928 %. This is due to the fact that, sometimes, the UAV has flown too far away from the cars. As for the adjusted 2D mobility model, the value rises up to 66.428 %. This is better as the UAV adjust its altitude, although it maintains its flight height with respect to the ground. The best value obtained is when we use the 3D mobility model. Using this model, the flight altitude is adapted according to the distance towards the cars on the ground. In fact, it offers the best overall connectivity when approaching the car measuring the lowest RSSI values, while maintaining an acceptable distance towards the remaining cars. Hence, although in terms of the average RSSI obtained, the adjusted 2D model may offer higher values, in terms of connected time, it does not perform as well.

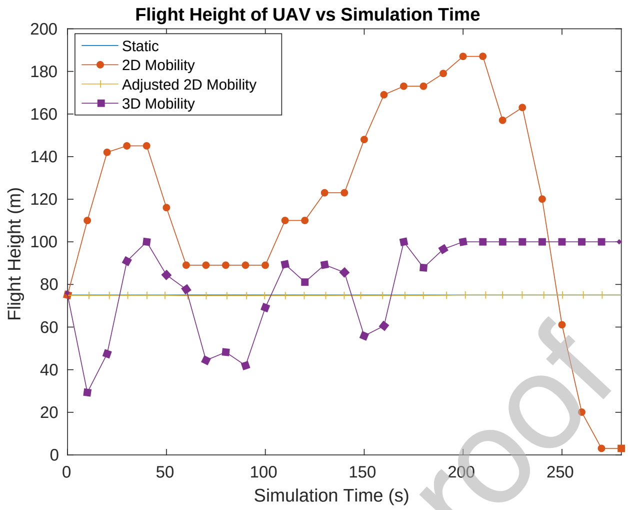


Figure 10: Height vs Time.

Table 2: Simulation Results.

Model	**Connected Time Percentage (%)**	**Average RSSI (dBm)**
Static	67.142	-87.827
Two-dimension	63.928	-90.132
Adjusted 2D	66.428	-84.336
Three-dimension	73.214	-86.932

6. Conclusions

This paper analyzes the mobility pattern of a UAV as support for car-to-car communications on the ground in the scope of a three-dimensional environment. A 3D mobility model was proposed in this paper that is specifically intended for a UAV attempting to maximize coverage throughout time. The model is defined by selecting the car that has the lowest signal quality received from the UAV as the transmitter, which then acts as a target point for the UAV's movement. This enables the UAV to transmit a balanced signal quality towards the cars on the ground, which is affected by the physical environment (terrain profile). The signal quality takes into account a special-purpose path loss model calculated with elevation information. This way, the mobility model is not only defined by the distance between the transmitter and the lowest receiver, but also considering the terrain blockages, which determines the optimal UAV location in terms of altitude.

We have tested the model in comparison with other three mobility models: a first model that only considers 2D space, a second model where the UAV maintains its flight height towards the ground, and a third model where the UAV remains static at a specific position. The results showed that, although in terms of the average RSSI the adjusted 2D mobility offered slightly better values, in terms of connection time, the 3D model outperforms the rest.

The work carried out can be extended by considering additional scenarios; for example, in an urban area or with buildings acting as obstacles, or when having a swarm of UAVs that can cooperate to achieve greater coverage in the presence of many ground vehicles.

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Acronyms

BSM	Basic Safety Messages
DEM	Digital Elevation Model
GPS	Global Positioning System
ITS	Intelligent Transport Systems
LOS	Line-of-Sight
NLOS	Non Line-of-Sight
OSM	Open Street Map
RSSI	Received Signal Strength Indicator
RSU	Road Side Unit
RWM	Random Waypoint Mobility
SRTM DEM	Shuttle Radar Topography Mission Digital Elevation Model
UAV	Unmanned Aerial Vehicle
UDP	User Datagram Protocol

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Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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