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Selection of Drone Locations to Act as Mobile Road-Side Units in An Intelligent Transportation System

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Abstract

Vehicular ad hoc networks have been used successfully in intelligent transportation systems for smart cities in recent years. However, the main obstacles to the widespread use of vehicular ad hoc networks are high packet collision rates, inflexible communication infrastructure, high routing overhead, unscalable networks, and inconsistent connectivity. Integrating vehicular ad hoc networks with uncrewed aerial vehicles (UAVs) offers a workable way around these obstacles. This paper presents a vehicular ad hoc network communication architecture supported by UAVs that serve as mobile roadside units (mRSUs), flying above the deployed region and providing communication services to the underlying coverage area. To determine the optimal locations for these drones to ensure continuous communication covering vehicles on intelligent transportation roads, three different optimization algorithms were used: Artificial Bee Colony (ABC), ant colony optimization (ACO), and particle swarm optimization (PSO). Skellam distribution has been used in optimization algorithms as a cost function. The impact of these new locations on throughput, packet delay, and packet loss was calculated. Among these three algorithms, the PSO algorithm showed higher throughput, lower packet delay and loss rates, and the best distribution of drone locations.

Keywords: Drone, Metaheuristic Algorithms, Skellam Distribution, Throughput, Vehicular Ad-Hoc Network.

1. Introduction

Intelligent Transport Systems (ITSs) are considered as one of the essential parts of an intelligent city. A recent development in wireless communications, namely the vehicle ad hoc network (VANET) [1] has made the implementation of an ITS possible. A VANET is an ad hoc network composed of vehicles capable of wirelessly communicating with road infrastructure (V2I) and/or other vehicles (V2V) [2]. The growing interest in VANETs and in the different uses and applications of smart devices and the Internet [3] is all gaining in popularity. It is a network with an unstable topology, meaning it changes all the time. Some vehicles rejoin the coverage area, while others leave the network, resulting in continuous changes in the nodes' positions [5]. Generally, VANET communication consists of two parts: the roadside unit (RSU) and the on-board unit (OBU). In the network architecture, the RSU acts as a router and is located on the roadside to support communication between vehicles. The OBU, on the other hand, is a radio device mounted in a vehicle that transmits and receives signals from other OBUs or RSUs [6].

VANET offers a solid communication structure for ITSs. The system is not flexible enough to cater to evolving access requirements, such as on-demand network infrastructure and extended coverage [7]. Multi-hop V2V communication can improve coverage and be dynamically added without infrastructure; however, it is limited and can reduce network performance [8]. Another major issue in VANET is scalability. The more nodes that are added, the less effective the network. This is because an excessive load on the network causes significant delays, too many packet collisions, and an increased routing table size [9].

The RSU is a stationary device that resembles a compact base station; however, it has a more limited coverage area. The RSU can communicate with automobiles via V2I. An optimal approach would involve installing RSUs to provide comprehensive coverage of the entire road network. Implementing RSUs requires high investment costs. Therefore, it will be fiscally infeasible to install RSUs across the entire road network [10].

Uncrewed aerial vehicles (drones)(UAVs) are a very intricate structure that integrates many equipment components such as a camera, Global Positioning System, controller, and specific software components including image processing, route planning[11]. UAVs that can collect data from a specific area and transmit it to ground VANETs, in the absence of direct multi-hop communication or in regions where infrastructure is difficult or prohibitively expensive to establish and maintain for optimal network coverage, may be used in conjunction with VANETs to address the aforementioned challenges [12].

This work proposes an architecture for UAV-assisted VANETs. UAVs have been employed to establish communication coverage in regions lacking adequate communication infrastructure. Several UAVs are flying and circling over the region where they are tasked with providing communication facilities in the proposed architecture. They can communicate with RSUs, vehicles, and nearby UAVs while operating as mobile RSUs (mRSUs). VANET assisted by UAVs has several benefits over conventional VANET:

Traditional VANETs rely on fixed, unconnected RSUs for communication. Traditional VANETs use fixed, unconnected RSUs for communication. But the execution and upkeep of RSUs could be costly, particularly in far-flung areas. The mobile RSU can overcome these shortcomings by using drones to create temporary or on-demand network connectivity at particular locations.

One of the advantages of using drones is their capability to maneuver in three dimensions, thereby improving network coverage. Drones can fly higher than autos, which significantly increases their communication range compared to fixed RSUs. The increased range allows vehicles that would otherwise be unable to connect due to distance or obstacles to connect.

Drone-to-vehicle communication can be achieved directly, without obstructions such as buildings, and without relying on line-of-sight communication. This provides more reliable, faster data transfer than when the data is obstructed by signals [13].

Moreover, three optimization algorithms (Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Particle Swarm Optimization (PSO)) are used to optimize the drones' locations. The Skellam distribution was used to determine the probability of connectivity. This is achieved by accounting for vehicle density (vehicle flow rate / average vehicle speed) and the distance between vehicles. These are important considerations for deploying drones as mobile roadside units [14]. The least likely connection was chosen to determine the drone's positions. The effect of the new location on throughput, packet delay, and packet loss was computed.

2. Related Works

The use of deployment strategies in wireless networks has proven advantageous for achieving optimal performance. Several strategies were used; however, the literature can generally be categorized into two distinct types: UAV-assisted deployment and RSU deployment.

In 2018, Ghorai and Banerjee [15] suggested that strategically placing RSUs in obstructed areas is essential for achieving complete coverage. In 2018, Yan et al. [16] presented an optimization technique for allocating resources and selecting shared access in scenarios where UAVs serve as airborne Base Stations. The terrestrial base station allocates its resources based on the UAV's access selection decision. Drones determine their choosing method based on the supplied communication resources.

Jiang et al. [17] proposed a 3D placement technique for UAVs in 2018 that optimizes coverage and throughput while accounting for the drones' memory constraints. The optimization problem is partitioned into two distinct components. The primary objective of the first section is to determine the most advantageous location for the drone, while the second portion focuses on devising an optimal caching technique.

In 2019, Pourbaba et. al. [18] suggested using a full-duplex UAV as a mobile relay to enhance coverage and connection in a full-duplex vehicular network. The UAV placement challenge was resolved by identifying the optimal site that effectively met the SINR criteria for all entities involved [18].

Oubbati et al. [19] introduced a new routing protocol for VANETs assisted by drones. The approach included using floods with route-expiry prediction and UAVs as relays to improve the dependability of data transmission and to handle path failures. Simulations showed an improved delivery ratio and reduced latency compared with current procedures. In addition, they investigated a UAV system for emergency response in urban areas.

In 2019, Sedjelmaci et al. [20] proposed a framework that uses UAVs to improve connectivity in dynamic vehicular networks. The proposed architecture employed game-theory-based prediction techniques to identify specific regions that required UAV relays. Additionally, a broadcast storm mitigation strategy was designed to conserve energy. Simulations showed that, compared to current methods, this method delivered packets faster, with less delay and less waste.

Nemer et. al. [21] examined the effective arrangement of UAVs in a network that assists at multiple levels and dimensions. The distributed technique was founded on a hypothetical game strategy. Furthermore, the utilization of self-organized behavior involved participation policies in each UAV's decision-making process.

Ackels et al. [22] examined infrastructure-based vehicular networks, with a specific focus on the deployment of RSUs in one section. However, it does not provide a classification of RSU deployment methods.

Ahmed et. al. [23] suggested a flexible Internet of Drones scheme for urban VANETs. This system deployed drones based on real-time vehicle locations to connect isolated vehicles and improve coverage. An improved PSO algorithm optimized drone placement for both coverage and connectivity.

Simulations showed better coverage and signal quality compared to RSU.

This paper proposes and tests three optimization algorithms for selecting the optimal location of an mRSU drone in a VANET: PSO, ACO, and ABC. This work builds upon existing research in drone placement optimization and in calculating quality metrics such as end-to-end delay, throughput, and packet loss rate, offering a comprehensive understanding of network conditions and ensuring optimal mRSU placement to enhance communication reliability and emergency response efficiency in VANETs.

3. Method of the Research

This work proposes a comprehensive network model consisting of several components to accurately depict the ever-changing structure of real-world ad-hoc networks, which can be characterized as follows:

- Communication Area: It is represented by a grid-based array that models the interconnected road network in the operational region. This enables the depiction of space and the modeling of movement.
- Vehicles: Vehicles are represented by moving points. They move along the roads according to a random walk model.
- Drones: They are represented as mobile nodes strategically placed in their most effective positions, as determined by the optimization algorithms being used.
- Network Infrastructure: It is represented by a set of links. The links connect the drones to the vehicles

The model is further parameterized, as shown in Table 1.

Table 1. Setup parameters.

Parameters	Value
Number of vehicles	20
Communication area	4 Km^2
Number of drones	5
Operating altitude of UAVs	100 m
Simulation time	300 s
Packet sent	1000 packet/s
IEEE standard	802.11p
V2V Communication Frequency	2.4 GHz [24]
Vehicle-to-UAV Communication Frequency	2.4 GHz

Skellam distribution as a cost function: The Skellam distribution represents the disparity between two uncorrelated random variables $\left(ʎ1(t) - ʎ2(t)\right)$. The Poisson distribution describes these two variables at various expected densities. Specifically, if ʎ denotes the vehicle density per Kilometer along an L-Kilometer Road, then the chance of having α vehicles on this route may be calculated as follows:

$$p(\alpha, ʎ\mathrm{L}) = \begin{cases} \frac{(ʎ\mathrm{L})^{\alpha}}{\alpha!} e^{-ʎ\mathrm{L}}, \alpha > 0 \\ 0,\ otherwise \end{cases} \tag{1}$$

The Poisson distribution of these two variables has distinct predicted densities. The vehicle density is unstable due to the dynamic mobility in a VANET topology, which affects route longevity and may disrupt communication continuity. Assume that at a certain point, the distance between two vehicles on a road is X. They can communicate with each other within a range of R. If the density of vehicles entering the coverage area between the two vehicles' source and destination is ʎ1. The density of vehicles leaving this area is ʎ2, then the probability that α vehicles are inside the communication range can be mathematically represented as:

$$p(\alpha; ʎ_1, ʎ_2) = f((ʎ_1 - ʎ_2)\mathrm{X})/R) \tag{2}$$

If α equals 1, then the probability that at least one vehicle will be able to cover the communication along a segment of road R is denoted by p. This value signifies the probability of connectivity and can be computed in the following manner using the Skellam distribution:

$$p(\alpha; ʎ_1, ʎ_2) = e^{-\left(\frac{(ʎ1+ʎ2)\mathrm{X}}{\mathrm{R}}\right)} \left(\frac{ʎ1}{ʎ2}\right)^{\frac{\alpha}{2}}\ \mathrm{I}_{|\alpha|}(2\mathrm{X}\sqrt{ʎ_1 ʎ_2}/R) \tag{3}$$

The symbol $I|k$ represents the modified Bessel function of the first kind and is defined as:

$$\mathrm{I}_{|\alpha|}\left(\frac{2\mathrm{X}\sqrt{ʎ_1 ʎ_2}}{R}\right) = \sum_{n=0}^{\infty} \frac{\left(\frac{\mathrm{X}\sqrt{ʎ_1 ʎ_2}}{R}\right)^{2n+\alpha}}{n!(n+2)!} \tag{4}$$

The Skellam distribution was utilized as a cost function to determine the lowest likelihood that connectivity would be chosen as a drone location.

To verify the efficiency and effectiveness of determining drone locations, the following measurements were adopted.

Throughput: The average number of packets transmitted per second.

$$Th = \frac{N*P}{\mathrm{T_{Sim}}} \tag{5}$$

The throughput (Th) is calculated by dividing the total number of data packets received (N) by the product of the packet size (P) and the simulation duration ($\mathrm{T_{Sim}}$).

End-to-End Packet delay: the mean time for a packet to travel between two vehicles.

$$EndtoEnd\ delay = \frac{1}{N}\sum_{n=1}^{N}(R_n - S_n) \tag{6}$$

Rn represents the time the nth data packet is received, Sn represents the time the nth data packet is transmitted, and N is the total number of data packets received.

Packet loss rate: refers to the proportion of packets that are not successfully delivered during transmission.

$$Packet\ Loss\ Rate = \frac{\text{Packets lost during transmission}}{\text{Total Transmissions}} = 1 - \frac{Succsesfull\ Deliveries}{Total\ Transmissions} \tag{7}$$

The proposed method was implemented in Python using the PyCharm IDE, taking into account the following steps:

- **Essential Libraries and Components:** To realize the proposed framework, the necessary libraries were imported, and crucial components instantiated. These included roads, vehicles, drones, and network infrastructure, which together formed the simulated VANET environment.

- **Simulation Setup and Initialization:** The simulation parameters were then established, defining the operational bounds and network characteristics. Vehicles and drones were strategically distributed within the communication area, adhering to a random placement model. Subsequently, the positions of vehicles at specific reference times were fixed to represent a snapshot of network dynamics.
- **Optimization Framework and Algorithms:** The core of the implementation lies in the optimization procedure for drone placement. Leveraging the Skellam Distribution as a cost function to identify locations with the lowest vehicle density and guide the drones to them, three prominent metaheuristic algorithms were employed: ABC, ACO, and PSO.

The implementation flowchart steps are shown in Fig. 1.

4. Results

Simulation results show the effect of locating the proposed UAV based on the optimized findings from the three metaheuristic algorithms used: PSO, ABC, and ACO.

The impact of varying population sizes on throughput, packet loss, and packet delay across the three algorithms was evaluated.

Fig. 2 shows the optimal distribution of drones in the communication area obtained using the PSO algorithm with a population size of 100.

Fig. 3 shows the packet loss for the three optimization algorithms across different population sizes.

As shown in Fig. 3, packet loss is lower with PSO than with ACO and ABC. This makes it better to determine the most appropriate location for the drone within this test.

Throughput was also calculated using the best drone locations determined by the three algorithms with various population sizes. The results are shown in Fig. 4. The recorded throughput for both the PSO and ACO algorithms is higher than that of the ABC algorithm.

As for the end-to-end delay results, the PSO algorithm is generally preferred, as shown in Fig. 5.

To examine the effectiveness of drones compared with fixed RSUs, vehicle locations in the network were determined for both the RSU- and drone-based scenarios. As shown in Fig. 6, the region was divided into four equal-sized quadrants, and a centralized RSU placement strategy was used to install one RSU at the center of each quadrant. The fifth RSU was located in the central region. The end-to-end delay, throughput, and packet loss rate were recorded to compare the fixed RSU and drone-based methods.

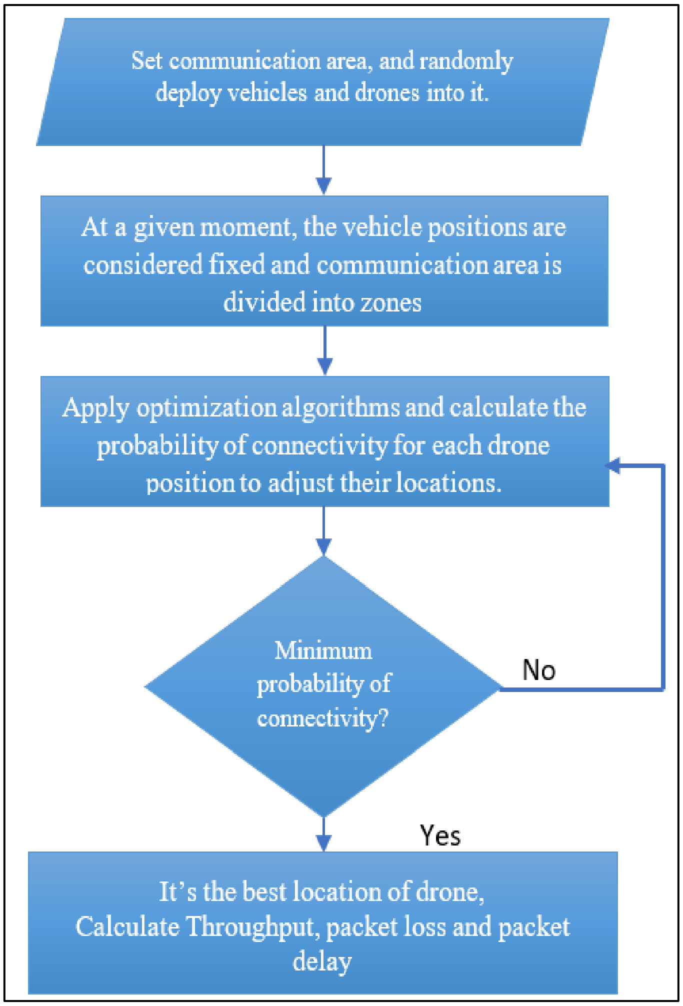

Figure 1. Flowchart of implementation steps.

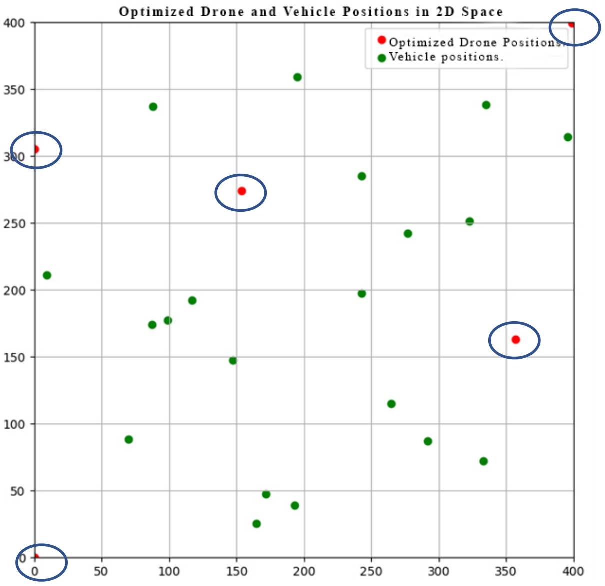

Figure 2. Optimized distribution of drones to ensure the best coverage of vehicles using PSO.

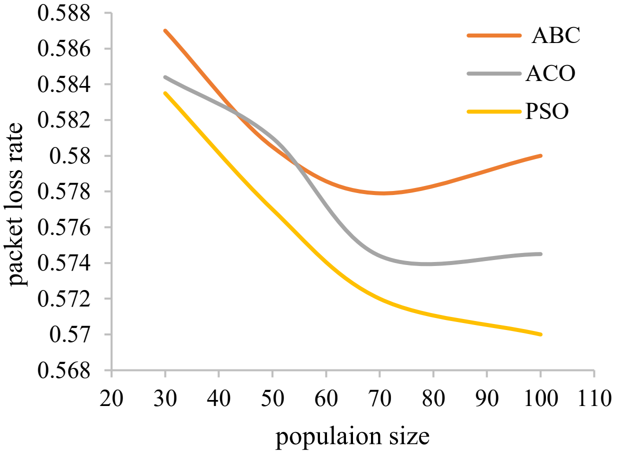

Figure 3. Packet loss rate.

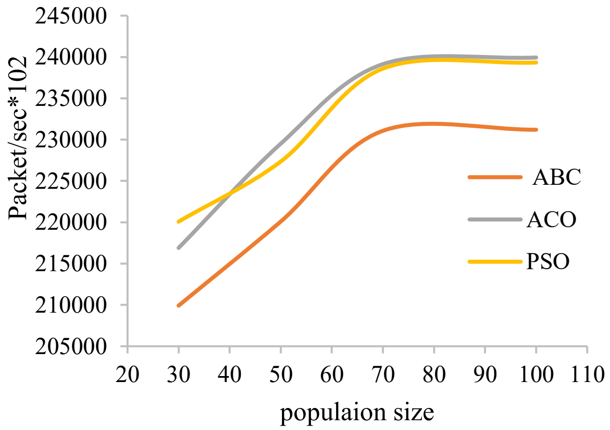

Figure 4. Throughput.

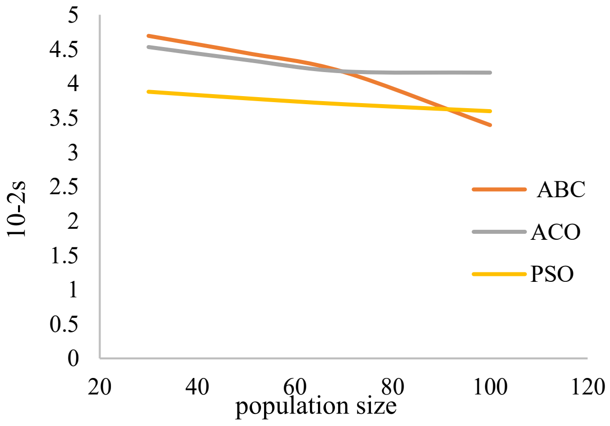

Figure 5. End-to-end delay.

Table 2 shows the performance metrics for drone- and fixed RSU-based scenarios.

The results show that drones with the PSO algorithm offer superior performance in VANETs compared to fixed RSUs. It reduced end-to-end delay by 37.78%, increased throughput by 21.32%, and reduced packet loss by 15.79%.

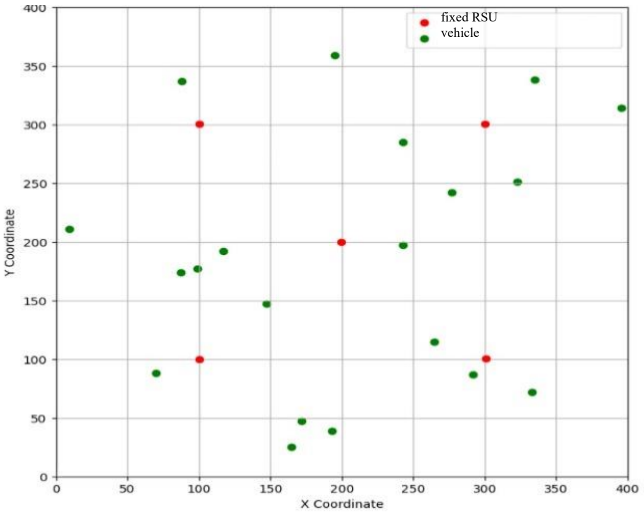

Figure 6. Distribution of fixed RSUs.

Table 2. Performance metrics for drones vs. fixed RSUs-based scenarios.

Scenario	**Packet loss rate**	**Throughput** Packet/sec	**End-to-end delay (sec)**
Drones with PSO algorithm	0.57	$23.9*10^{6}$	$3.59*10^{-2}$
Fixed RSU	0.66	$19.7 *10^{6}$	$5.77 *10^{-2}$

5. Discussion

The results from the experimental data show that the optimization method used has a significant effect on the success of deploying a roadside unit (RSU) via an unmanned aerial vehicle (UAV) in VANET scenarios. The results of the three algorithms investigated, including PSO, were consistently the best in terms of packet loss, throughput, and end-to-end delay, indicating that PSO has a superior ability to establish optimal drone locations across different traffic densities.

For all algorithms, it is observed that packet loss decreases with increasing number of vehicles, as shown in Figure 3. This is because, in densely trafficked situations, the number of communication channels between vehicles and UAVs increases, leading to better network connectivity. As node density increased, all algorithms performed better, but PSO exhibited the lowest packet loss across the experiments. The swarm intelligence mechanism of PSO enables efficient information exchange within the swarm while guiding particles towards the globally optimal solution, reducing the likelihood of selecting suboptimal UAV positions. ABC, on the other hand, had the highest packet loss rate, since the exploration strategy was sometimes slower but still converged, whereas ACO had slightly better results due to its pheromone-based exploration strategy.

The throughput results presented in Figure 4 clearly show that throughput increased with population size until around 70–80 vehicles, after which the improvement leveled off. As seen in this saturation behavior, once a sufficient level of network connectivity is reached, additional vehicles cannot provide much greater communication capacity, as the network has reached its practical limit. At higher population sizes, both PSO and ACO yielded similar throughput, whereas ABC generally demonstrated lower throughput, attributed to higher packet loss and lower drone positioning efficiency.

The end-to-end delay shown in Figure 5 generally decreased with network size, while ABC and ACO exhibited comparatively larger delays. Shorter UAV placement routing paths, better connections, and fewer retransmissions due to better UAV placement are the primary reasons for lower delay. The PSO algorithm successfully reduced the communication distance between vehicles and UAVs, thereby reducing communication delays. The ACO delay values remained constant, but its convergence time in the optimization process was longer than PSO's, resulting in inferior performance compared to PSO.

As summarized in Table 2, these benefits of mobile UAV deployment are further evident when comparing the drone-assisted communication system with traditional fixed RSUs. The use of drone-based RSUs led to a reduction of approximately 15.8% in the number of lost packets, an increase in throughput of more than 21%, and a decrease in end-to-end delay of nearly 38% compared with fixed RSUs. The improvements highlight UAVs' ability to adapt their position to traffic distribution, ensuring greater network connectivity than a static one. This flexibility is especially useful in emergency situations, temporary events, disaster recovery operations, and highly dynamic urban traffic, where it is difficult to maintain consistent coverage with traditional RSUs.

The results obtained from the PSO-optimized antenna placement match those reported in most other UAV placement and VANET optimization studies, in which PSO has often been found to converge quickly and to possess good global search capability. The same performance has been observed in other application areas, such as wireless sensor network deployment and UAV path optimization; in these applications, PSO can balance exploration and exploitation to achieve optimal communication configurations. While the achieved competitive throughput values are promising, the computational complexity and the slow convergence rate may limit the applicability of ACO in rapidly changing VANET environments. Similarly, ABC gave satisfactory answers, but showed more variability in its communication performance.

While these encouraging results have been reported, several potential limitations should be noted. The simulations employed idealized communication conditions, a simplified vehicle mobility model, and were based on the assumption of ideal UAV maneuverability. The deployment of VANETs in the real world involves additional factors to consider, including signal fading, wireless interference, obstacles, weather conditions, UAV battery life, and regulatory flight limitations, which can impact network performance. Moreover, the number of optimization algorithms explored was limited to three, and other newly developed metaheuristic and hybrid algorithms are expected to yield further performance gains.

In general, results demonstrate that the combination of UAV-RSUs and intelligent optimization algorithms can significantly improve the quality of VANET communication. All the examined performance metrics are superior with PSO, indicating that this method is a promising choice for real-time UAV applications in the intelligent transportation system.

The results of this study show that VANET performance can be improved by optimizing UAV deployment while maintaining the same number of communication nodes. PSO-based UAV positioning could be used by transportation agencies for emergency management as a temporary communication infrastructure during traffic congestion, road construction, natural disasters, and large public events. The proposed framework can also help enhance communication reliability in future connected autonomous vehicle (CAV) systems. This hands-on insight adds to the engineering relevance of the studies.

6. Conclusions

This research was an attempt to explore the use of metaheuristic optimization algorithms to find the optimal placement of UAV based Roadside Units (RSU) into Vehicular Ad Hoc Networks (VANETs). The Particle Swarm Optimization (PSO) algorithm, Artificial Bee Colony (ABC) algorithm and Ant Colony Optimization (ACO) algorithm were used to optimize the location of the drones and the Skellam distribution was applied to estimate the probability of vehicle connectivity within the communication area, so a network model was created. The evaluation of network performance was based on packet loss, throughput, and end-to-end delay for various numbers of vehicles.

The simulation results showed that using UAV-assisted communication can also significantly enhance network performance compared with conventional fixed RSUs. PSO had the best overall performance among the investigated optimization techniques, offering the lowest packet loss and end-to-end delay, as well as the highest throughput, across different traffic densities. Although ACO achieved competitive throughput, it was still found to be inferior to PSO in terms of communication reliability and delay. The ABC algorithm had the least overall performance as it generated the most dropped packets and the lowest throughput. The results also showed that the more vehicles there are, the denser the vehicle network, the more the network performance improves, but the improvement gradually diminishes as the communication network becomes saturated.

The advantages of mobile communication infrastructure in dynamic vehicular environments were confirmed by comparing optimized drone deployment with fixed RSUs. The proposed approach successfully reduced packet loss, increased throughput, and decreased communication delay by adjusting UAV position based on traffic distribution, thereby demonstrating its effectiveness in increasing the communication reliability of the ITS.

Overall, the results show that PSO is an effective and strong optimization method for UAV placement in VANETs and it is a potential approach to improve the communication quality in highly dynamic road networks. The proposed framework could be further enhanced in future by exploring hybrid optimization algorithms, considering realistic urban mobility models, wireless channel impairments, UAV energy constraints, and adaptive real-time deployment strategies to strengthen the applicability of the proposed framework to real-world intelligent transportation systems.

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Abbreviations

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ITSs	Intelligent Transport Systems
mRSUs	Mobile Roadside Unit
OBU	On-Board Unit
PSO	Particle Swarm Optimization
RSU	Roadside Unit
UAVs	Uncrewed Aerial Vehicles
VANET	Vehicle Ad Hoc Network
V2I	Vehicle-to-Infrastructure Communication
V2V	Vehicle-to-Vehicle Communication

Conflict of interest

“The authors declare that there are no conflicts of interest regarding the publication of this manuscript”.

Author Contribution Statement

Huda Adel Talib proposed the research problem, developed the theory, and performed the computations.

Mohammed Ali Tawfeeq verified the analytical methods and supervised the work's findings.

All authors have read and agreed to the published version of the manuscript.

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