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Article

Enhancing Routing Efficiency in UAV-Assisted Vehicular Networks Via Integrating Fog Computing and Software-Defined Networking

Saif Thamer Mohammed Museedi[1], Hardik Joshi[2]

[1]Ph.d student, Department of computer science Gujarat University
Email: saif.thamer@gujaratuniversity.ac.in
[2]Associate Professor (Computer Sc.), Department of Computer Science, Gujarat University
Email: hardikjoshi@gujaratuniversity.ac.in

Abstract: Unmanned aerial vehicles (UAVs) have been used in heterogeneous vehicular networks to enhance performance on extremely congested roads and areas with low coverage. Nevertheless, when aerial relays are added to the routing process, the routing occurred in a more complex environment. Routing protocols often favour UAV relay routes because UAV relay route can have better link quality and a small number of hops, but the routes developed from these routing protocols can lead to load imbalance between the aerial and terrestrial elements of the network and sometimes the UAV can be the bottleneck itself. This paper aims to utilize modern networking paradigms, i.e., Software-Defined Networking (SDN) and Fog Computing—to achieve routing operations in a heterogeneous, cluster-based Vehicular Ad Hoc Network (VANET). Fog nodes will take responsibility for offloading/performing the computational tasks involved in cluster formation, inter-segment routing between the aerial and terrestrial paths, and determining the optimal number of cluster heads. Fog nodes will use fuzzy logic and reinforcement learning to execute these tasks. The role of the SDN controller will be to manage traffic flow across fog cells using its global view of the multi-tiered network architecture which integrates heterogeneous vehicles with fog-layer connectivity. The proposed model was assessed visa a variety of routing protocols designed for UAV (Unmanned Aerial Vehicle)-assisted networks as well all routings used in traditional vehicular networks in several scenarios. The performance has proven to be far superior in a variety of aspects, including: the packet delivery ratio as a function of vehicle density and the aerial relay density; network utilization efficacy as a function of the harvesting node speed; and end-to-end delay as a function of ground node density. Finally, the results provide strong evidence on the success of the selective clustering method taken up in our model, as based on the dwell time of the cluster.
Keywords: VANET, Unmanned Aerial Vehicles (UAV), Fuzzy Logic, Reinforcement Learning, Software-Defined Networking (SDN), Fog Computing, Congestion

1. Introduction

Vehicular networks are considered an essential component of intelligent transportation systems (ITS). Yet, the extra mobility of their nodes regularly leads to fast and unpredictable changes in network topology. Consequently, data transmission is complicated which in turn results in a negative communication delay [1–3]. Roadside Units (RSUs) are usually utilized to make communication between vehicles and infrastructure easier, improving coverage and connectivity. Nonetheless, the costs incurred from deploying and maintaining many RSUs can be substantial, which motivates the deployment of Unmanned Aerial Vehicles (UAVs) as relay nodes in Vehicular Ad-Hoc Networks (VANETs) [4]. UAVs provide some benefits, including on-board processing, high-precision localization, feasibility of reconfiguration to maintain line-of-sight (LOS) links while avoiding obstacles, and the capacity to perform sensing and wireless communications in the same physical platform. These features make UAVs a very viable, cost-effective option as a substitute for fixed RSUs, especially when contrasted with the establishment of large scale ground infrastructure [5].

Even though, congestion may occur in the UAV relay networks (URN) since routing protocols frequently favor air links due to their superior link competence and lower hop count. Such preference may lead to traffic imbalance under heavy ground-network load, potentially resulting in the UAVs themselves becoming a constraint to communication. Alternatively, considering that a ground-based link may fail, using aerial relays as backup route may not be the best option, since it can lead to underutilized resources [6].

Recently, VANETs have started to adopt new networking techniques, to better the quality of routing performance. Methods such as vehicle clustering [7-9] have been proposed to reduce the overhead of routing, while Software-Defined Networking (SDN) [10-12] can "see" the network metrics and control the network in a centralized way. Fog Computing [13,14] was proposed to provide low-latency computing support close to vehicles to perform timely computations in dynamic scenarios.

Based on these developments, the current work proposes a hybrid architecture which combines Software Defined Networking (SDN) and Fog Computing for alleviating the negative effects of congestion in the ground segment of a UAV-assisted heterogeneous VANET. The approach aims to avoid bottlenecking aerial relays and induce data-priority differentiation to maintain Service Quality (QoS) and stability.

At the fog layer, two parallel operational processes are performed. The first concerns vehicle clustering within the ground segment, where each fog cell employs fuzzy logic to determine the optimal number of cluster heads. Cluster heads are then selected based on predicted mobility stability, followed by cluster formation that accounts for link reliability, signal-to-interference-plus-noise ratio (SINR), and data type. The second process, at the fog level, handles data routing between the aerial and terrestrial layers by using reinforcement learning, which dynamically defines routing policies, depending on a data priority and cost of congestion in the road segment.

At the same time, SDN controller is a higher-level abstraction that allows to manage inter-fog routing policies based on the fog-cell loads.

The rest of this paper is structured as follows: Literature Review that forms the theoretical foundation of the proposed work is provided in Section 2. Then the fundamentals of the research in terms of the mathematical equations associated with the implementation of the proposed mechanism, the reinforcement learning algorithm to find routing-policy thresholds to select aerial relays, and the fuzzy logic system are detailed to identify optimal cluster heads to use depending on vehicle density in Section 3. Afterwards, a detailed flow diagram is presented to illustrate the proposed framework in Section 4. Section 5 displays the main findings of the simulation setup and results. Finally, the conclusion is presented in Section 6.

2. Literature Review

In study [15], a new routing protocol is presented to improve routing performance in a Vehicular Ad Hoc Network (VANET) using a spectral clustering method for vehicles. The study sought to decrease the routing overhead and to keep stable clusters for a longer period by leveraging Software-Defined Networking (SDN). SDN was set to improve the limitations of traditional clustering methods that fail to analyse real-time data, which can lead to failure to reach even a single optimum requirement for intra-cluster routing and, as a result, degrade the overall QoS. The proposed model also used Deep Reinforcement Learning (DRL) to select paths between clusters and its use of the Deep Deterministic Policy Gradient (DDPG) algorithm to allow for continuous learning within high-dimensional action spaces typically encountered in vehicular networks.

In Study [16], it was mentioned that Unmanned Aerial Vehicles (UAVs) could be employed as relay nodes within a highly dynamic vehicular network. The study aimed to maximize the network throughput, by queuing packets off congested ground vehicles back to the aerial relay, before the ground vehicles became too congested. The UAVs essentially had to estimate the load on ground vehicles at low cost and with low overhead. The UAVs calculated a ground congestion index (as a basis for activating the UAV to relay packets) based on the length of vehicular queues, in addition to an aerial congestion index for essentially triggering the traffic management for congestion situations. The routing decision policy was provided via Q-learning algorithm, where the routing action was computed from the current state of the network (i.e., the congestion indicators). The decision policy considered packet priority and ground-based routes upon the decision to trigger the aerial relay nodes. Study [16] proposed a hierarchical routing scheme in vehicular-aeronautical network (VANETs) whereby -- roadside units (RSUs) were assigned the task of selecting next road intersections for packet forwarding packet using Q-learning. Each RSU maintained a Q-value table containing the possible actions to be taken up to each investigated RSU, corresponding to the road segments leading to the next anticipated road intersections. The Q-values were updated in real time based on the rewards provided. The second level routing occurred across road segments and was grouped into three phases. The first involved inter-vehicle routing where the source vehicle selected the next representative vehicle for further routing using a greedy method based on Euclidean distance. While the best representative was evaluated by considering the destination point, it was identified by either the target vehicle itself, the point for the driver indicated by the RSU level algorithm, or another intersection based on its proximity. The destination point was searched for in the neighbour table of the vehicle, which listed neighbour id's, speeds, and positions. If the destination point was found in the neighbour table, data were sent directly to that vehicle. If it was not found, the closest neighbour and fasted speed were determined to find the next best vehicle. If there weren't suitable neighbours available in the neighbour table, a fuzzy logic based retry process was activated, which was also the second level routing. This allowed the RSU to send data via the network to the closest or fast moving vehicle in the table heading to the destination location beyond the road segment. The rerouting process brought into play I2V routing. After the next intersection was identified for the data to reach, the RSU performing routing then send the data directly to the vehicle, if it was within range, or an alternate route via a vehicle who was closest to the intersection from the two previous routing methods.

Study [17] sought to create an improved routing protocol for VANETs that would predict future distances between destination nodes and neighboring nodes using Recurrent Neural Networks (RNNs) and Linear Predictive Coding (LPC). The objective was to find stable and reliable routes. The operation of the mechanism was that once the destination node received the first request to route, it would trigger a waiting timer, which would allow the destination node to receive other requests from other neighboring routes. After the time expired, the destination would compute a mobility index for each node that requested the route based on the predicted distances, and it would take the request cost into consideration to create a new overall cost index. The destination would use the overall cost index to select the neighboring node that had the lowest cost, and then the request would be sent to that neighboring node using the optimal reverse path back to the based station, while the destination could reject those requests with less stability. By using this selective retransmission, it was found that routing overhead was reduced while the packet delivery ratios improved.

In [18], a routing protocol for heterogeneous VANETs was presented, in which UAVs served as relay nodes. The routing protocol supported two routing modes: intra-cluster routing using an altered density-based clustering algorithm, and inter-cluster routing. RSUs and UAVs use table-driven routing for low latency, whereas vehicles used opportunistic routing to get closer to a higher reliability level as mitigator for techniques using tables. The paper took into consideration UAV path planning optimization for the lower latency in route, leading to higher network accessibility and packet delivery ratios while still respecting latency limitations.

The findings of study [19] include a multi-objective routing protocol for Vehicle Ad-Hoc Networks (VANETs), implementing a Dynamic Topology Evolution (DTE) approach to generate routing decisions. In this approach, the reliability and signal-to-interference-plus-noise ratio (SINR) of network links between vehicles were also taken into account to estimate the effectiveness of each link based on pre-defined thresholds. The main advantage of the DTE routing scheme is that it only uses the reliability and SINR metrics of the active links to apply the Dijkstra algorithm to choose the most optimal transmission paths with the minimum number of hops, which is less processor-intensive than a routing approach using machine learning that generates outcomes from extensive training data and aims to apply complex algorithms.

Study [20] presented a routing mechanism designed to reduce the control overhead imposed on RSUs in SDN-enabled vehicular networks. This routing mechanism was developed with the suggestion of a vehicle clustering strategy in which clusters would have one member becoming the cluster head and assume part of the control actions by identifying routes for the member vehicles. If this cluster head fails, then this request will be redirected to the RSUs, or, if necessary, to the cloud storage unit. This mechanism has reduced expectations resulting in less control workload on the RSUs, but it has introduced challenges with optimal selection of the cluster-head (e.g., the influence of the selection on the stability of the cluster). Consequently, a multi-criteria decision-making method was used and the Analytic Hierarchy Process (AHP) was used to weight the criteria for selection, while the final candidate selection was made using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

Finally, in [21] vehicle rerouting was considered for avoiding congested road segments using an Internet-of-things based fog computing framework. Each road segment from one intersection to the next was assigned a cost value that indicates the level of congestion on the road segment based on several parameters: Average waiting time, average gas emissions, and density of vehicles. Fog nodes would have to perform calculations to arrive at a cost, and vehicles would choose the next-hop route according to the cost. Vehicles also provided occasional real-time data to fog nodes at the intersections that would update the metrics to be used. In case of unexpected events such as an accident or road maintenance, vehicles would inform the fog nodes, and the fog nodes would inform a centralized server in order to take the appropriate action based on the type of even.

3. Research Fundamentals

In this paper we propose a network architecture formed of three hierarchical layers: a heterogeneous vehicular network, a set of fog nodes, and a SDN controller. These layers work together to allow for efficient routing operations between the terrestrial and aerial components of the heterogeneous network.

In this context, a variety of techniques, algorithms, and mathematical formulations are used for optimizing routing performance, reducing congestion, and positively affecting communications reliability. In the subsections that follow, the specific aspects, operational dynamics, and mathematical models within the proposed system are described in detail.

3.1 Equations Used in the Proposed Framework

The equations used in this work can be classified into two main categories regarding their overall function. The first category refers to the criteria used for cluster formation; the second category refers to the metrics used for congestion detection and for optimal load balancing in the land-based air and terrestrial portions of the vehicular network.

3.1.1 Criteria for Cluster Formation

Firstly, we introduce the mathematical formulation for the criterion by which the cluster heads are selected, called the mobility/movement index. This index is based on both the Euclidean distances that are recorded in the past between a node and its neighbors and the estimated distances produced by deep learning algorithms (RNN [22]) combined with the Linear Predictive Coding (LPC) approach [23]. The mean and variance of both recorded and predicted distances wis calculated for each method after finishing the time segment defining. The resultant mobility index, after the calculations, will be generated with ($MI_{N_i}^{LPC}$ □ $MI_{N_i}^{RNN}$) generated—the mobility index generated from the RNN—and the mobility index generated from LPC successively, as presented in [17]:

$$= \alpha MI_{N_i}^{RNN} + \beta MI_{N_i}^{LPC} \qquad (1) MI_{N_i}^{Combined}$$

The connection between the vehicle and the cluster head, which is considered the mobility-stable of the candidate nodes (the lowest mobility index), will be established based on one parameter related to the data type sent in conjunction with two other criteria:

- **Link Reliability**, that is defined as the prospect that the communication link between the vehicle seeking to join the cluster and the selected cluster head remains available over a specified time interval. This metric is calculated according to the relationship [18] as follows:

$$= \frac{erf\left(\frac{\mu_r - 2R_{eff}/t + T_P}{\sqrt{2}\ \sigma_r}\right) - erf\left(\frac{\mu_r - 2R_{eff}/t}{\sqrt{2}\ \mu_r}\right)}{2} \qquad (2) r_{hi}$$

Accordingly, $T_P$represents the estimated link duration, calculated as the ratio of the sum of the effective transmission range $R_{eff}$and the Euclidean distance between the cluster member and the cluster head, to their relative speed, $N(\mu_r, \sigma_r)$.

- The **Signal-to-Interference-plus-Noise Ratio (SINR)** guarantees error-free data transmission over the communication link when it goes over a predefined threshold. It is calculated as follows according to the relation [19]:

$$(3) SNIR_{n,t+\tau} = \frac{p_t L_{hn,t+\tau}}{I_{n,t+\tau}}$$

The two symbols $p_t$and $L_{hn,t+\tau}$ refer to the transmission power of the cluster head node and the propagation loss, correspondingly, while $I_{n,t+\tau}$signifies the interference experienced by the vehicle candidate attempting to join the cluster.

It is important to consider the number of cluster heads within a fog cell coverage area. This calculation is based on two input factors: the average congestion cost associated with stretches of road in the coverage area, discussed in Section 3.1.2, and the average communication quality of vehicles within the fog cell.

The communication quality between two vehicles $i$and $j$is mathematically represented as a weighted average of two factors: the contact duration λ_{ij}, which reflects link stability, and the average reception rate of hello messages η_{ij}, which signifies the link reliability. This relationship is calculated according to [16] as follows:

$$(4) CQ_{I,j} = \frac{\omega_1 \lambda_{ij} + (\omega_1 - 1)\ \eta_{ij}}{\sum_{vehicle\ j \in Neighbor\ i} \ \omega_1 \lambda_{ij} + (\omega_1 - 1)\ \eta_{ij}}$$

The symbol $\omega_1$represents the weighting factor, which ranges between 0 and 1, while Neighbor i refers to all the neighboring vehicles of the vehicle i.

3.1.2 Criteria for Rerouting

Regarding the cost of the road segment, representing the level of congestion, it is employed as a key metric for rerouting decisions—both within the terrestrial network and between terrestrial segments and aerial relays, whether intra-cell or inter-cell within the fog computing layer. This cost for a given road segment $w_x$is formally computed as in the following relationship [21]:

$$C(W,X)= \alpha\ \underline{wait_{wx}}+ \beta\ \underline{em_{wx}}+ \frac{\gamma}{\tau_{wx}} \quad (5)$$

The cost of the road segment indicates the congestion level and is used as a principal factor in rerouting decisions, whether inside the terrestrial network or between terrestrial streams in fog computing and aerial relay (whether inter- or intra-cell). The cost for a segment of road w_x is mathematically expressed as follows [21]:

The cost is a linear function of the average expected delay of vehicles in the road segment (("wait") ̅_(w_x)) and the average expected emission (("em") ̅_(w_x)). The traffic flow condition (τ_(w_x)) is a function of the capacity of the road segment and is inversely related to the cost. The summation of parameters α, β, and γ is normalized as one.

As far as load balancing between terrestrial and aerial networks is concerned, the framework computes the average congestion index of terrestrial nodes, which is computed by fog nodes whenever they needed the required data from the aerial relay nodes. The average congestion index is defined as a ratio between the number of congested nodes and the total number of nodes, N(t). A vehicle is considered congested if GNCI〖_i〗(t) is equal to one, meaning that the weighted average of the load in the waiting queue has exceeded a given threshold. The queue load for each vehicle is calculated as the ratio of the average queue length during a given time interval and the maximum queue length allowed. The average terrestrial congestion index can then be expressed as follows [6]:

$$=\frac{\sum_{i=1}^{N} \quad GNCI_i(t)}{N(t)} \qquad (6) GNCI_{Ratio}$$

In the same manner, the aerial relays determine their congestion index, URCI_u (t), as a function of the average queue length AQL_u related to the maximum queue length MQL_u as follows [6]:

$$=\frac{AQL_u}{MQL_u} \qquad (7) UNCI_u$$

3.2 Q-Learning Algorithm

In this article, we also employ Q-learning algorithm [6,24], where the fog nodes are acting as agents for the UAV relays in this design. The intent of this design is to lessen the computational burden of a UAV due to its limitations on usable resources (e.g. energy), by limiting the role of the UAV to communicate the information of the network environment. The information being communicated by the UAV includes a state, that is describing the congestion index of the aerial node and the average terrestrial network congestion index. Unlike [6], we are using fog nodes at the edge of the heterogeneous vehicular network to perform the Q-learning algorithm, which has a more intensive amount of calculations needed.

Upon observing the network state, the algorithm selects an action expected to yield a reward, which is subsequently used to determine the optimal routing policies. These actions correspond to a parameter called the UAV Routing Policy Area (URPA), which is defined by upper and lower bounds representing threshold values for applying different UAV routing strategies. Naturally, these bounds correspond to the minimum and maximum congestion index values of the aerial relays. The dynamic adaptation of the URPA bounds is intended to maintain the maximum permissible routing through UAV relays while ensuring an acceptable level of data traffic within the terrestrial segment of the heterogeneous vehicular network [6].

With respect to the routing policies, the framework we proposed has three separate policies. The first policy is invoked whenever the lower bound of the Unmanned Aerial Vehicle Routing Policy Area (URPA 〖_Lower) satisfies URPA_Lower≤UNCI_u. This policy allows the utilization of the aerial path regardless of the type or priority of the transmitted data (low, medium, or high) as well, regardless of the availability of terrestrial routes.

The second routing policy is utilized when the condition URPA_Lower is met. In this policy, aerial node routing is employed if the terrestrial routing path has a congested segment, as indicated by C(W,X), or if the link reliability deviates beyond the predetermined threshold due to an increase in vehicle speed. The policy also considers the priority of the data being sent: there are the data with very high priority that require immediate delivery (Urgent Service, USM) and data with medium priority (Real-Time-Service, RTS) that is acceptable of a minor packet loss but has delay constraints on delivery.

The third routing policy takes effect when UNCI_u>URPA_Upper. In this routing policy, only high-priority data can be sent, and that data is subject to congestion costs on the road segments along the terrestrial routing path. The routing policies we propose in this study consider congestion along the entire path for the source to destination. It seems to improve both delay and packet loss for data types that have stringent constraints on either or both delay and loss, which was not considered in [6].

3.3 Fuzzy Logic Technique

The suggested framework takes into account the influence of increased vehicle density on the cluster size and the need to find the optimal quantity of cluster heads to maintain the desired quality of service. To do this, the fog nodes periodically invoke a fuzzy logic system [25] to reason about selecting the proper number of cluster heads under the current network condition.

The fuzzy system takes two inputs: the average congestion cost of road segments within the fog cell, denoted as $Avg\_C(W, X)$, and the average communication quality among vehicles within those segments, denoted as Avg_CQ_{wx}.

Triangular membership functions are applied to assign membership degrees to the crisp input values, converting them into fuzzy values. The inference engine then evaluates a set of nine rules, organized according to the fuzzy rule base, as presented in Table 1. According to the system, the output—representing the number of cluster heads—is converted from its fuzzy form into a crisp value through the defuzzification component, using the Center of Gravity (CoG) method.

Table 1: Rule Base

Intput		**Output**
Avg_C(W,X)	**Avg_CQwx**	**Number of Cluster heads**
low	poor	moderate
low	fair	few
low	good	few
medium	poor	many
medium	fair	moderate
medium	good	moderate
high	poor	many
high	fair	many
high	good	many

4. Proposed Framework

The suggested framework examines a heterogeneous vehicular network wherein unmanned aerial vehicles (UAVs) operate as aerial relays. The operation of the framework, as represented in Figure (1), is designed in three tiers. The first tier is made up of the ground vehicular network, which consists of groups of vehicles. The fog nodes, which operate as the second layer of the architecture, perform both clustering the vehicles by finding a proper number of cluster heads with fuzzy logic, and then clustering itself by selecting cluster heads and vehicle members.

The selection of the cluster head is based on the mobility index of the vehicles from the predicted Euclidean distances so that the choice is made from among the most stable and highest mobility vehicle. The selection of cluster members is considered from three perspectives: the link reliability, the link signal-to-interference-plus-noise ratio (SINR), and the type of data being transmitted. The Analytic Hierarchy Process (AHP) is utilized to weight these parameters, in order to take into account their impact on clustering on the basis of network performance. Therefore, clustering is considered a selective process which values quality over quantity to enhance cluster stability.

This method allows fog nodes to have a full perspective of network congestion across road segments covered by fog. This perspective is used to route data through aerial relays rather than terrestrial relays or reroute traffic to road segments with comparatively lower utilization, informed by reinforcement learning and policies that they defined. Decisions also consider the terrestrial and aerial indices of congestion, cost of road segment coverage in the fog, and reliability of links. Moreover, the use of aerial relays is not restricted to relieving terrestrial congestion or performing load balancing, as we still consider overhead relays when sending delay-sensitive data (e.g., emergency messages). Therefore, the type of data that we are working with has an impact on the decision to use an aerial route.

The software-defined network (SDN) controller is located at the third level and has a global view of the heterogeneous vehicular network and the fog cells. This allows for efficient data routing between fog cells. The SDN controller will tell each fog controller about any congestion in adjacent coverage areas and instruct the controllers to route data from the least congested neighbouring cell. The SDN controller also computes the metrics of delay and packet loss for each data flow in a fog cell along the routing path to support data prioritization and quality-of-service (QoS) needs as it relates to load in fog cells. This further enables cognitive awareness for fog controllers to consider the SDN controller's resource allotments and reroute data flows through aerial relays, rather than terrestrial relays, to minimize the possibility of congestion when approaching threshold limits.

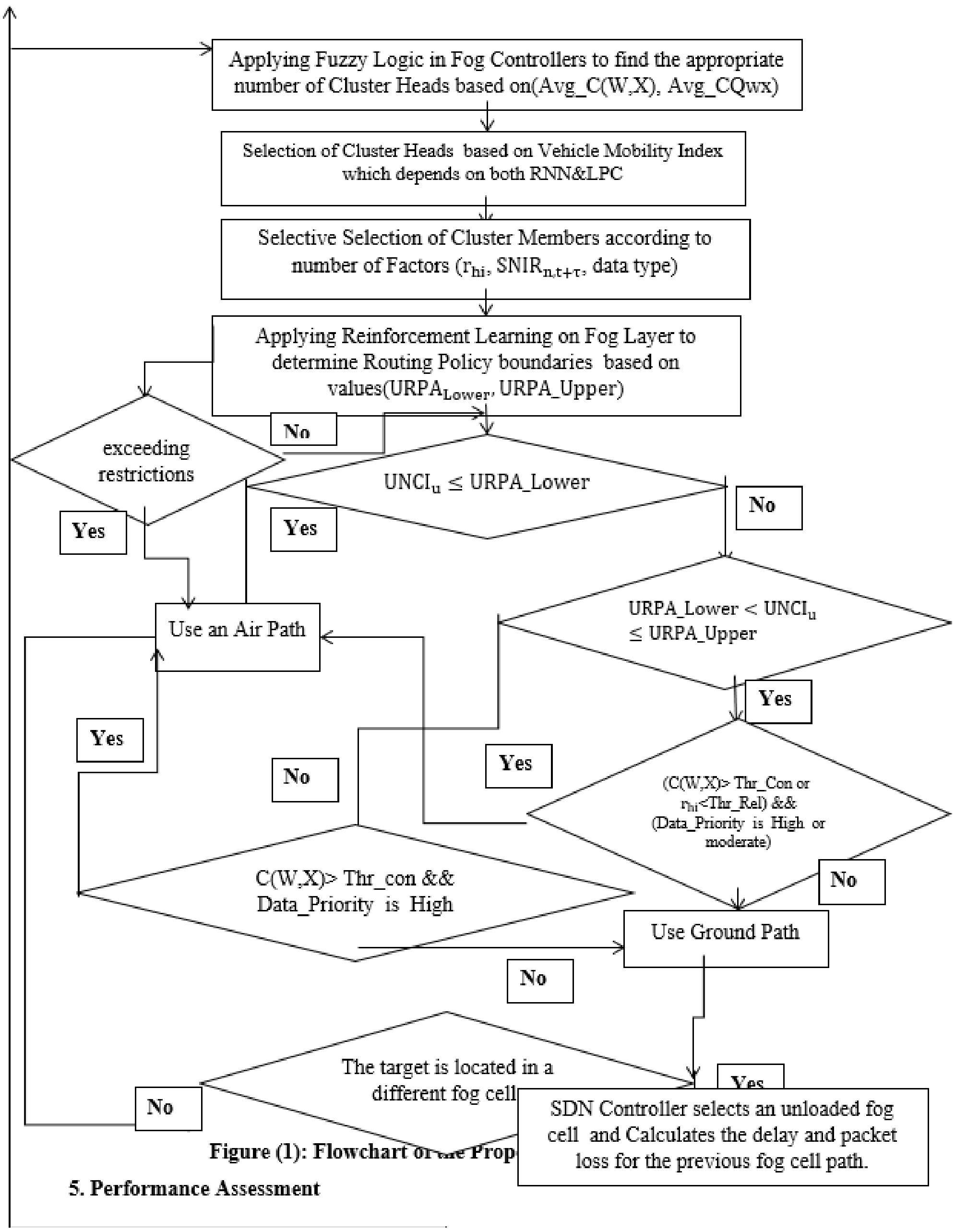

Figure (1): Flowchart of the Prop

5. Performance Assessment

The NS-3 simulator was used to assess the performance of the proposed framework against the ADMR protocol for routing using UAVs and a cluster-based routing approach [18], the Q-LBR protocol, which uses aerial relays, to balance the load [6], and the technique in [21] employing fog computing to route between road segments, avoiding congested segments of road. Fixed simulation parameters applied to the simulations across scenarios are shown in Table (2).

The varying parameters of the simulations include, number of vehicles, varying from 50, 100, 500, 1000, 2000, and 4000; number of UAVs including, 2, 4, 6, and 8; and vehicle speeds constant at 36 km/h, 72 km/h, 108 km/h, and 144 km/h. Finally, reported results represent the average from 10 simulation runs.

Table (2): Simulation Parameters

Parameter	Value
Mac Protocol	802.11P
Q-Learning-Learning Rate	0.3
Q-Learning-Discount Factor	0.7
Propagation Loss Model	Urban Propagation Model
Frequency Band	5.9 GHZ
Dimensions of the Network	4Km*4Km
α, β, γ (Constants of Cost)	0.33,0.33,0.34
Threshold of SINR	10 db
Threshold of Reliability	0.6
Application-USM traffic(Size/Rate)	Exp.256 bytes/ Exp.10 rps
Application –RTS traffic(Size/Rate)	Con. 1500 bytes/Con. 10 rps
Application-COP traffic(Size/Rate)	Exp. 256 bytes/Exp. 10 rps
Simulation Time	1000 Sec

The results presented in Figure (2) indicate that the suggested approach can attain a better packet delivery ratio (PDR) than the remaining routing protocols being considered especially when the number of vehicles in the network becomes more dense. As a rule of thumb, the PDR will decrease for all protocols while the network becomes more congested due to increased contention for the wireless medium and an increased likelihood of collision, which leads to packet loss.

There are three important elements in its operation which explain the efficacy of the proposed approach, that minimize congestion. First, UAVs are used as auxiliary relays in support of terrestrial relays, following prior routing policies. Second, fog nodes oversee the rerouting of vehicles toward lower congested road segments and within the fog coverage. Third, the SDN controller is responsible for inter-fog-cell traffic management considering congestion indices and costs associated with the certain road segments.

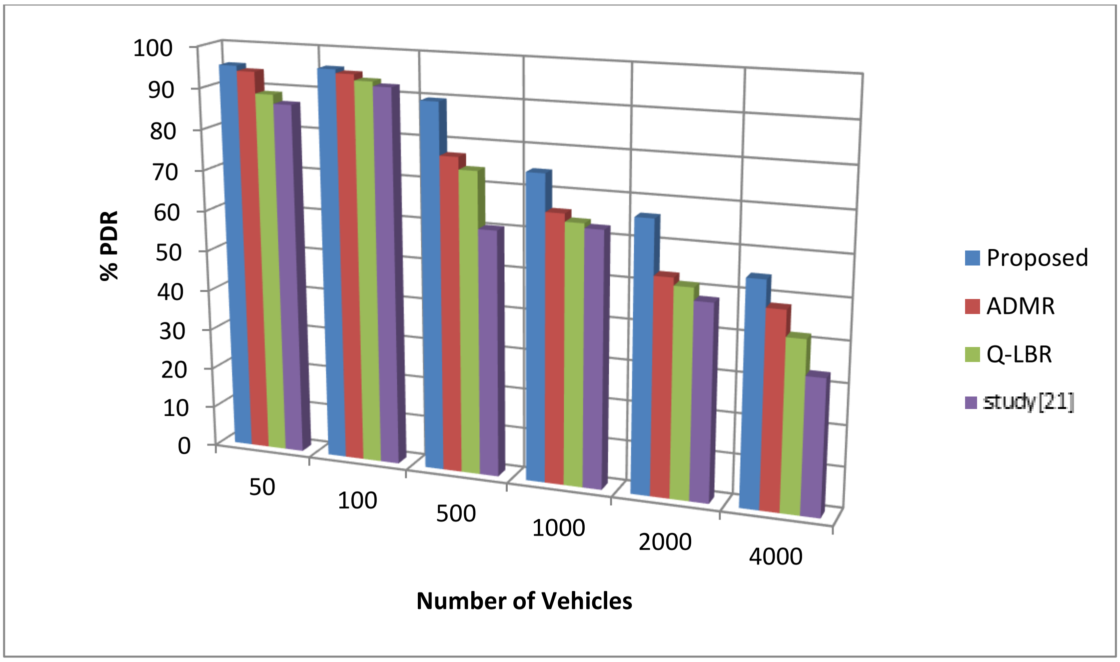

Figure (2): Packet Delivery Ratio (PDR) as a Function of Increasing Vehicle Density

The data in Figure (2) illustrates that the proposed approach can achieve a higher packet delivery ratio (PDR) as compared to the other routing protocols outlined in this work particularly as the density of vehicles increases. As a general guideline, the PDR will decline for all protocols as the network becomes denser due to greater contention for the wireless medium and a greater likelihood of collision, leading to packet loss. There are three key elements to its operation that reduce congestion. First, UAVs are used as extra relays that support urban relays following prior routing protocols. Second, fog nodes manage the rerouting of vehicles to segment roads with less congestion and inside the fog coverage. Third, the SDN controller is in charge of managing all inter-fog-cell traffic considering congestion indices and costs associated with the appropriate segment of the road.

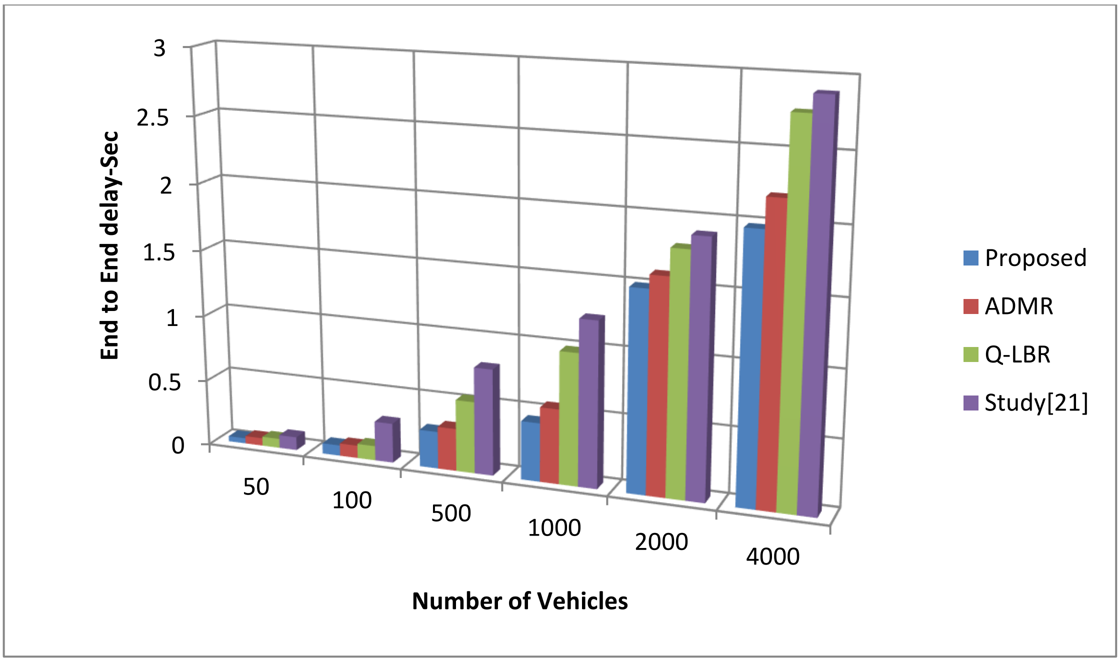

Figure (3): Delay as a function of increasing vehicle density

The findings illustrated in Figure (4) demonstrate that the proposed method yields the highest packet delivery ratio (PDR) with each additional UAV in the heterogeneous network. This higher performance is due to the architecture's ability to effectively resolve both congestion-related issues and QoS demands of certain data types to improve the utilization of aerial relays and increase network accessibility.

The ADMR protocol is the second-best in terms of packet delivery ratio (PDR). While it uses clustering and aims to create a heterogeneous network similar to our proposal, it has no means to visualize the entire network at a global level, limiting its ability to fully take advantage of the aerial relays. The Q-LBR protocol, which follows ADMR, attempts to balance load between terrestrial and aerial relays, however it does not take into account path planning for aerial network components or look at the network holistically to increase medium access. Finally, the method presented in [21] had the lowest PDR value as it did not leverage UAVs, which is why the delivery ratio was constant despite variation in parameters related to the scenarios.

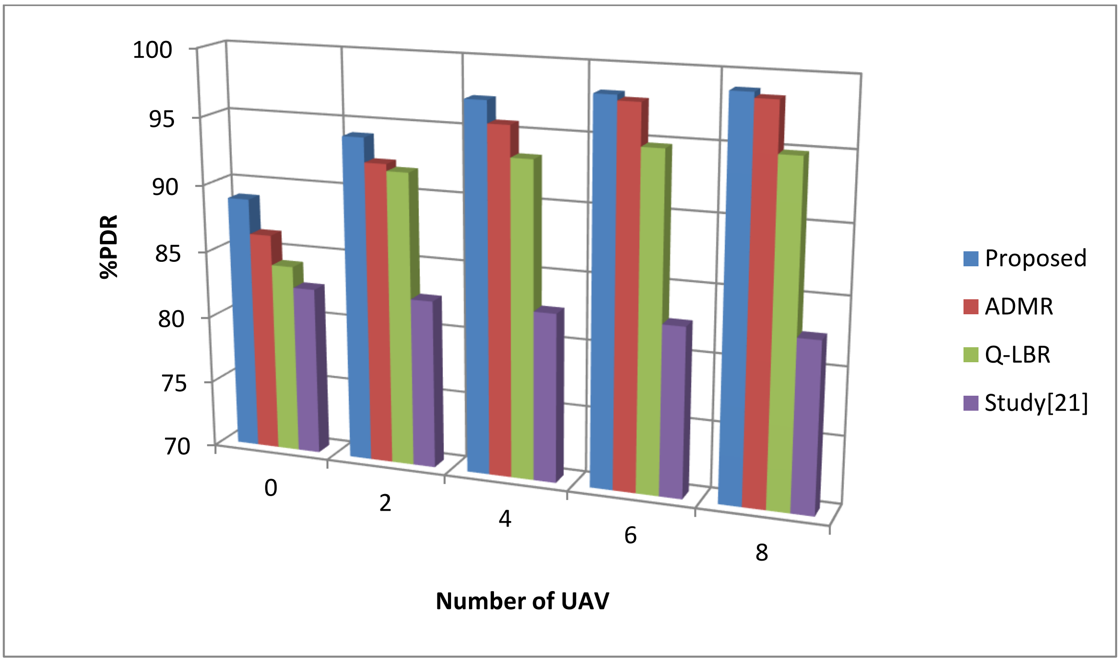

Figure (4): Packet Delivery Ratio as a Function of the Number of UAVs

One consideration in our proposed method is the cluster formation technique, which is a characteristic of the ADMR protocol, while the studies in references [6] and [21] do not consider this and therefore were not included in the average cluster lifetime over time comparison drawn in Figure (5). In fact, the metrics used in average cluster lifetime indicate the resilience of the vehicle clustering approach. The results support our proposal in that we have shown clusters to be strong and have extended lifetime of communication between members and the cluster head, which is selected based on its stability in motion using RNN and LPC. Furthermore, cluster member selections are made based on criteria designed to enhance cluster quality of service. The ADMR protocol on the other hand relies on a modified density-based clustering algorithm, called MDBSCAN.

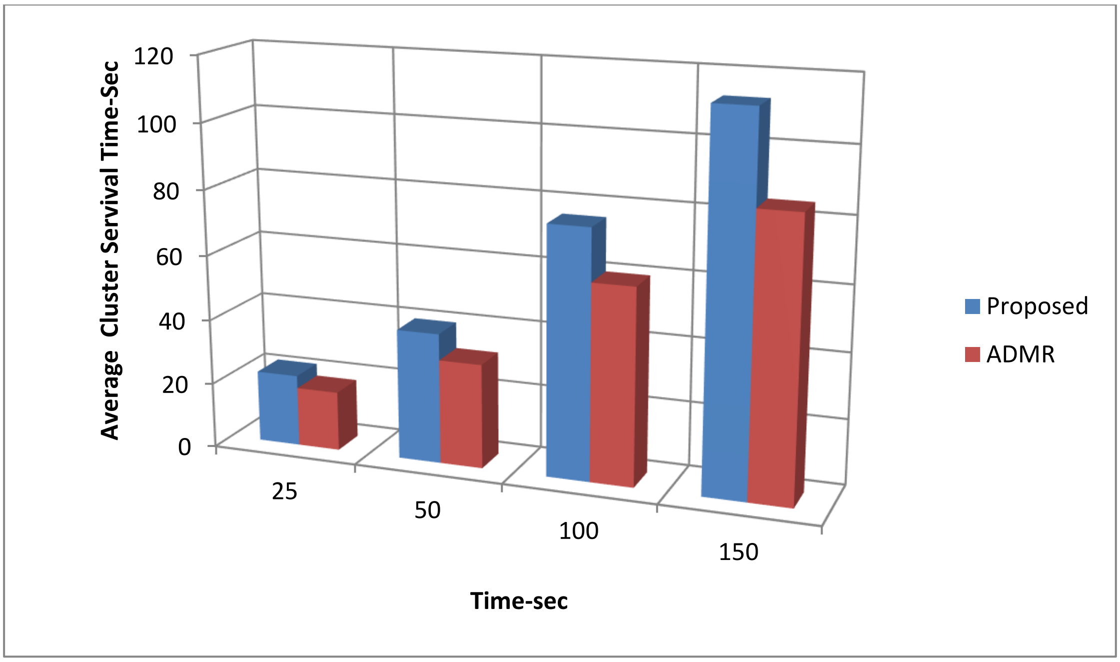

Figure (5): Average Cluster Lifetime as a Function of Time

As revealed in figure [6], the network utilization ratio decreases with the speed of the vehicle in the protocols using UAVs as air relay nodes (i.e., the proposed protocol, ADMR, and Q-LBR) at narrowly decreasing rates. However, this decrease is more significant at very high speeds, which demonstrates a clear advantage to using UAVs. In a homogeneous VANET, the efficiency ratio increases with vehicle speed due to unstable links and frequent rerouting which was clear in the results from the previous study, [21]. The proposed protocol had a better utilization rate than other UAV-based protocols at significantly increased vehicle speeds, demonstrating its capability to balance loads between terrain and aerial networks. Other heterogenous network protocols declined utilization rates, and rather used UAVs to achieve shorter-hop paths than terrestrial rerouting, which was their desired effect in order to maintain high quality links.

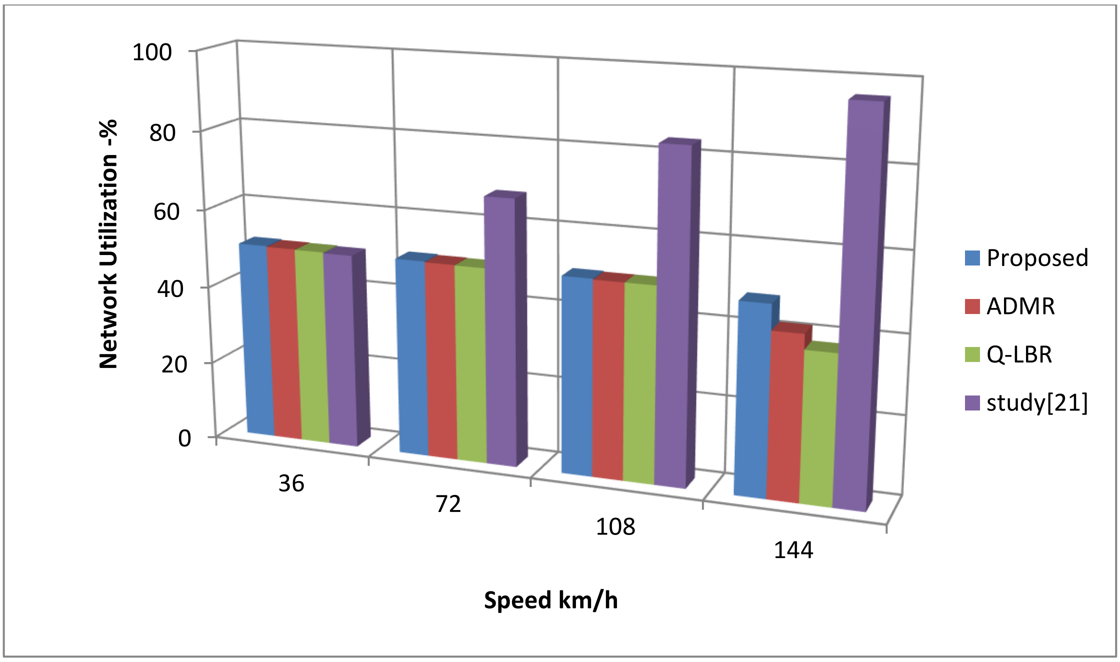

Figure (6): Percentage of Network Utilization with Increasing Vehicle Speeds

6. Conclusion

To conclude, this study relies on incorporating fog computing to enable selective vehicle clustering and routing when connecting the terrestrial network with aerial relay depending on congestion and priority of data. Also, we incorporate a software-defined network (SDN) to enable efficient routing in fog coverage areas according to their load.

The assessed findings come in align with the proposed framework with enhancements to the quality of service in heterogeneous vehicular networks by increasing packet delivery ratios and reducing end-to-end delay along the routing paths. This framework also provides more utilization of network components by equally balancing the use of highly accessible aerial paths (due to their low latency) to less desired land-based paths to decrease the usage of precious resources. Particularly, this method of routing clustering will also create a stable network along with less overhead against routing through a multi-criteria creation approach.

Based on the findings, the research suggests deploying this network architecture and routing approach in congested urban environments or in places where high-priority data transmissions are necessary since the approach intentionally assesses data priority.

In future studies clustering aerial relays may be considered to offload the load sharing aspect among the aerial relays or optimization of UAV routing using machine learning approaches for data load predictions. Predictive approaches can adjust paths dynamically considering UAVs' energy limitations to optimize time in operation. In addition, machine learning models might also be developed to predict UAV speed and altitude to help maintain stable connectivity with highly mobile ground platforms.

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