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Obstacle detection to minimize delay and Q-learning to improve routing efficiency in VANET

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ABSTRACT

Nowadays, several service providers in urban areas significantly consider vehicular ad hoc networks (VANET). VANETs can enhance road safety, prevent accidents, and grant passengers entertainment. Though in VANET, efficient routing has remained an open problem. VANET is dynamic; the frequent update in the situation originates through several aspects, such as traffic conditions and updates in the road topology, which demand a suitably adaptive routing. The existence of blocking obstacles degrades routing approaches and increases the failure of paths. These issues build an excessive amount of resource utilization and increase network delay. To solve these issues, obstacle detection to minimize delay and Q-learning to improve routing efficiency (ODQI) in VANET is proposed. This mechanism uses the spanning tree algorithm detects the obstacle. Clustering can be used to manage the topology in VANETs. The dingo algorithm selects the best cluster head (CH) based on vehicle bandwidth, speed, and link lifespan. Furthermore, the sender forwards the traffic information from the sender to the receiver by applying a Q-learning algorithm. This learning algorithm computes the award function to choose the forwarder, improving the routing efficiency. Simulation results demonstrate that the ODQI mechanism increases the CH lifetime and minimizes the network delay.

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1. INTRODUCTION

With a high relative speed of the vehicles and frequent network discontinuity, vehicular ad hoc networks (VANETs) have a very dynamic topology [1]. The roadside units (RSUs) enable communication between vehicles and infrastructure and redirect packets when a link is lost [2]. The vehicle moves in an identical direction, and each vehicle may transmit with another vehicle if both are in the communication range of each other vehicle [3]. If other vehicles are not within the communication range, the vehicles can communicate directly with the RSU [4]. In VANET, every vehicle can communicate by applying IEEE 802.11p and dedicated short-range communication (DSRC) standards (i.e., 100-500m) communication range [5]. By restricting the broadcast to a chosen set of vehicles, the clustering strategy may lower the routing cost and increase the scalability of the network [6]. The more successful the clustering, the better the topology control [7]. Each cluster has a cluster head (CH) that connects with the external controlling stations, such as the RSU. The process of creating and maintaining clusters is distributed [8]. However, cluster creation is several challenges are presented in an urban scenario, as the deep crossing of roads, concrete structures, and heavy vehicle density cause changeable topology and movement with time dependence. Another significant problem is the need for better communication links. The dingo algorithm is established on the dingos hunting behavior which contains surrounding, tracking, as well as attacking the target. This algorithm offers less computational cost [9]. The dingo algorithm-based forwarder choice mechanism to improve network performance [10].

Problem statement: hypergraph clustering model (HGCM) for the urban scenario mechanism is an evolving hypergraph to account for their dynamic nature and the frequent establishment and breakdown of node connections [11]. For each cluster, it is advised to use the relative velocity score, eccentricity, neighborhood degree, and trust score to locate the CH with the least volatility. Compared to the performance of the three existing measures, for example, relative speed, eccentricity, and neighborhood, the inclusion of the trust component in average CH stability significantly improves the results. The method is tested on many integrated network metrics using a one-hop network setup. However, this mechanism raises the computational complexity. When traveling at higher speeds, the CH stability of the network degrades. To solve these issues, obstacle detection to minimize delay and Q-learning to improve routing efficiency in VANET is proposed.

The use of a hybrid optimization strategy to choose the best CH is suggested by the combination of a multi-objective genetic algorithm and a gravitational search algorithm [12]. This strategy will likely consider various goals, including load balancing, network coverage, energy efficiency, and other pertinent metrics. Internet of things (IoT) networks often use cluster-based routing to increase scalability and efficiency [13]. It entails segmenting the network into clusters, with a CH normally in charge of directing communication within each cluster. Based on the social behavior of dingoes, the dingo optimization method is a metaheuristic optimization method inspired by nature. It attempts to resolve efficiency issues by mimicking the behavior of dingoes during communication and hunting.

VANETs allow for communication between vehicles and infrastructure, enabling a number of uses, including traffic control, collision avoidance, and information sharing [14]. Vehicles provide a lot of data on VANETs, which may be used for a variety of things, such as enhancing traffic flow and enhancing road safety. Federated learning is a strategy that permits group model training without centralized data aggregation. It enables a network of edge devices to train models locally on their own data before sharing model updates with a central server or with other network nodes. This method addresses privacy issues and lessens the requirement for data transfer, which might be helpful in vehicle settings where network capacity and data privacy are major considerations.

Self-organizing VANETs refer to networks where vehicles autonomously organize themselves into a network without relying on a centralized infrastructure [15]. These networks enable communication between vehicles and infrastructure for various applications, including traffic management, collision avoidance, and cooperative driving. An anti-collision algorithm in the context typically aims to reduce the likelihood of collisions between vehicles by enabling efficient communication and coordination [16]. Deep learning involves training artificial neural networks to learn and make predictions or decisions from complex data. An anti-collision algorithm for self-organizing VANETs that utilizes deep learning techniques. It may propose a neural network architecture, training methodology, or data processing techniques that enable vehicles to make collision predictions or take appropriate actions to avoid collisions.

Highway cluster density and average speed prediction mechanisms in which enable diverse applications, including traffic management, collision avoidance, and information transmission [17]. Average speed is the average velocity of a vehicle in a given area, while cluster density is the number of clusters created by vehicles in a certain area. The ability to predict these variables might be useful for resource allocation and proactive decision-making in traffic management and planning.

The load balancing and min-max fairness in vehicle-to-vehicle (V2V) compute offloading inside VANETs seem to be the paper’s main points [18]. To increase efficiency or get around resource constraints, computational offloading is the act of moving computing duties from one device to another. Vehicles may cooperate and share computing work to improve the performance of the whole system. The goal of load balancing is to fairly divide the computational effort across the participating resources or cars, preventing any one resource or vehicle from being overwhelmed while others are left underused. The idea of “min-max fairness” aims to make participation equally equitable by reducing the greatest possible variation in performance or resource consumption. In order to achieve load balancing and min-max fairness in V2V, compute offloading inside VANETs. It could suggest a solution that takes into account things like the amount of resources that are available, the computing power of the vehicles, the state of the network, and how the workload is distributed across the vehicles. A multi-objective strategy based on deep learning and differential evolution algorithms that uses both deep learning and differential evolution approaches to tackle various goals in VANETs [19]. The effective distribution of data, resource allocation, routing, and security are only a few of the difficulties that VANETs face. The authors want to create a method that may concurrently maximize many goals by combining the advantages of differential evolution with deep learning.

Hypergraph clustering includes categorizing information or items based on their connections, where connections are not restricted to pairwise connections but may occur between a number of entities at once [20]. It enables the data to be captured with more intricate connections and linkages. Urban settings provide unique difficulties in the context of VANETs because of the high vehicle density, intricate road systems, and shifting traffic patterns. By grouping the vehicles according to their geographic closeness, traffic patterns, or other pertinent characteristics, clustering may assist in this process. This mechanism may take into account a variety of variables, including vehicle locations, velocities, communication patterns, and other contextual data, to build hyperedges that represent interactions between vehicles.

To automatically and dynamically infer the shape of static obstacles standing, utilize a technique called autonomic obstacle detection and avoidance [21]. Automatic obstacle recognition using a coverage-to-precision ratio to identify fixed, convex obstructions. To successfully achieve our goal of autonomously avoiding broken connections induced by the blocking barrier, the suggested detection approach offers a suitable precision ratio without requiring “a priori” knowledge of the obstacle map. But, in this approach, routing stability is lesser. Obstacle prediction-based routing protocol for detecting vehicles, sending packets to the RSU, and selecting the most reliable path [22]. Improving packet delivery rates by updating prediction routing protocol to use reliable paths and including new logic in selecting intermediate nodes on the way to the destination. After modifying the predictive greedy and predictive perimeter forwarding algorithms to fulfill the criteria, they are used in this mechanism as the forwarding and recovery algorithms, respectively. However, this mechanism raises the routing overhead [23]. A number of analytical approaches to build unfailing route formation. Though, the wireless medium is untrustworthy [24]. An obstacle aware mobile sink path strategy mechanism to detects the obstacles that improve the lifetime [25]. Assistive model of obstacle detection by applying deep learning algorithm [26]. Bacterial behaviour algorithm is used to measure the location of obstacles in an unidentified situation. However, this mechanism s expensive [27].

2. PROPOSED METHOD

For simulating urban scenarios, we utilized road traffic situations and a clustering structure for VANETs. This vehicle transmission offers stable inter-vehicle communication and demonstrates the best routes to the receiver. The traffic dynamics assist in maximizing the performance of routing by utilizing velocity, acceleration, and traffic movement. However, a vehicle’s acceleration and speed both influence how it moves. To avoid accidents, a safe parameter is utilized to conceive safety criteria. Figure 1 demonstrates the block diagram of the obstacle detection to minimize delay and Q-learning to improve routing efficiency (ODQI) approach. This figure contains three phases that are CH selection, obstacle detection, and forwarding data. Here, CH selection is followed by dingo algorithm, and we detect the position of the obstacle by spanning tree algorithm. Finally, the Q-learning algorithm is used for forwarding traffic information from sender to receiver.

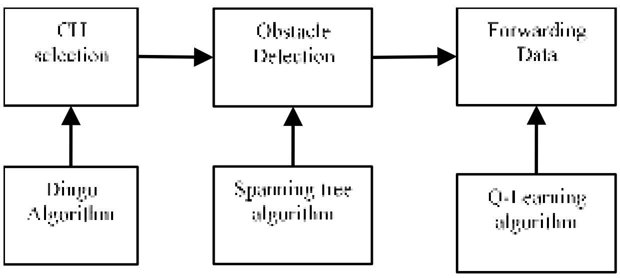

Figure 1. Block diagram of the ODQI approach

2.1. Cluster formation

In VANETs, clustering acts as a significant task in grouping vehicles with the same features and limiting needless broadcasts. The topological scenario entropy is shared with the vehicles using RSUs. The most common measurements are mobility and neighborhood; however, in an urban environment where vehicles go at a slow pace, and there is heavy traffic during rush hours, these measures are lost. Since the topology of the VANET is constantly shifting, connecting one source to the intended vehicle can be difficult. Data loss can be significant if the connection is multi-hop because the carrying vehicle may alter its course and speed. Accordingly, the information should be delivered in a single hop, which is doable by constructing a dependable cluster. A CH is chosen by the surrounding nodes. The CH-annotated vehicle is in charge of increasing the network performance in addition to producing clusters with more efficiency.

2.2. CH selection

Choosing a CH with a lengthy cluster lifespan is the main problem of VANET clustering strategies. The dingo algorithm is used to discover the CH. Dingoes have accurate reporting, and they communicate with each other cluster members by detecting some parameters. In this system, dingo makes sound feedback; the dingoes replace their information with others. The amplitude of the excitement is updated by the durability of the person as the dingo motions into a new location from the previous one. Cluster search is a pertaining behavior of dingoes that constructs its extension to the behavior of dingoes. Figure 2 illustrates the dingo algorithm-based CH selection.

Figure 2. Dingo based CH selection in VANET

The dingo's algorithm function is categorized as: surrounding, tracking, and attacking the target. Dingoes are capable of finding out the location of the target. After tracing the location, the group adopted by alpha circles the target. It is accepted that the accessible best agent is the target that is similar to the optimal because the chase region is not identified a priori.

Surrounding: dingoes often congregate in clusters while hunting. Dingoes have the ability to locate their target and encircle it. In (1) represents this behavior. Here, $\vec{x_j}(t+1)$ represents the search agent's new location that denotes the movement of dingos, and n indicates the arbitrary movement of $2, \frac{pop\ size}{2}$. Where pop size denotes the dingo's population size. $\overrightarrow{\lambda_h(t)}$ represents the search agent subset, $\vec{x_j}(t)$ denotes the present search agent, and $\vec{x} * (t)$ represents the optimal search agent. η_1 represents the arbitrary number equivalently rendered in the interval of [−2,2].

$$\vec{x_j}(t+1) = \eta_1 \sum_{h=1}^{n} \frac{\left[\overrightarrow{\lambda_h(t)} - \vec{x_j}\right]}{n} - \vec{x_j} * (t) \quad (1)$$

Tracking: dingoes often pursue tiny prey until each individual animal is captured. This behavior is modeled by (2). Where $\beta 2$ represents the arbitrary number consistently created in the interval of [−1,1]. In addition, r_1 indicates the arbitrary number created in the interval from 1 to the highest of search agents (dingoes), and $\overrightarrow{x_{r1}}$ represents the selected r^{th} search agent.

$$\vec{x_j}(t+1) = \vec{x_j} * (t) + \eta_1 * e^{\eta_1} * \left(\overrightarrow{x_{r1}}(t) - \vec{x_j}(t)\right) \quad (2)$$

Attacking the target: when dingoes are wandering aimlessly across their area, this function is described as the behavior they engage in order to obtain carrion to consume. This behavior is modeled by (3). Where υ represents the arbitrarily created binary number. Furthermore, it computes the fitness function based on vehicle bandwidth, vehicle speed, and link lifespan. The dingo viability rate calculation is specified (4).

$$\vec{x_j}(t+1) = \frac{1}{2}\left[e^{\eta_1} * \left(\overrightarrow{x_{r1}}(t) - (-1)^{v} * \vec{x_j}(t)\right)\right] \quad (3)$$

$$viability\ rate(j) = \frac{Fit_{max-}Fit_{(j)}}{Fit_{max-}Fit_{min}} \quad (4)$$

where Fit_{max} and Fit_{min} are the most horrible, and the optimal fitness value in the present creation, correspondingly, but $Fit_{(j)}$ represents the j^{th} search agent present fitness value. The viability rate contains the fitness in the interval of [0,1]. In (5) is applied for low viability rates, e.g., for viability rate values equal to or less than 0.5.

$$\vec{x_j}(t) = \vec{x_j} * (t)\frac{1}{2}\left[e^{\eta_1} * \left(\overrightarrow{x_{r1}}(t) - (-1)^{v} * \overrightarrow{x_{r1}}(t)\right)\right] \quad (5)$$

2.3. Obstacle detection

The environment contains different shape obstacles. Here, the spanning tree algorithm is applied to detecting the obstacle. The obstacle-detecting spanning graph contains rest of edges, which can be planned via building connections between vehicles and bends of obstacle. Figure 3 explicates the vertices of vehicles and isolates an obstacle bend represently.

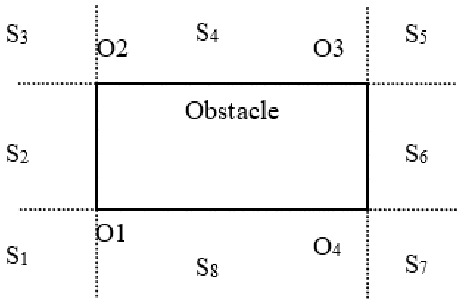

Figure 3. Obstacle bends with vehicle vertices

Equally, the section S4 and S8 are obstacle bends but, here sort elements of the list V by non-decreasing y coordinates in the region R4 and R8 of all obstacle corners. In addition, the section S4 and S5 of obstacle bends, the region S1 and S3 of connect vertices. We sort components of the list V by non- minifying x+y coordinates in the section S1 and S5 of obstacle bends and the region S1 and S3 of connecting vertices. Likewise, the section S3 and S7 of the entire obstacle bends and the region S2 and S4 of connect vertices. Here, the components of the list V are sorted through non-minifying y-x coordinates. Along with the quadrant division for an obstacle bend and a trapped vertex, then lastly make the spanning graph. Accordingly, the spanning graph to determine an obstacle and form an obstacle aware routing.

2.4. Route formation

The sender recognizes all routes, then we confirm the Q-learning algorithm for the efficient route from sender to receiver. Every vehicle function as an agent, cooperatively sharing information with other CHs to ensure that every CH is aware of the state transmission behavior. The ODQI components are as follows {S, A, AW, P}. Where S indicates the state, A represents the action, AW refers to the award, and P denotes the communication possibility. Assume PS denotes the present state, NS refers to the next state, and the present state action acts as the. Let t indicate the waiting time for information transmits to select the next CH. In Q-learning, the QV-table value aids in describing an every-state action, and the action value function Q (S, A) permits the AWs of present and next when action A is performed at state S. We think that the agent selects an action in S, discovers AW and goes into next state NS. Next, the QV, Q (S, A) is depicted as (6).

$$QV(S,A) - (1-\delta)QV(PS,A) + \delta\{AW + \sigma.QV(NS,A)\} \quad (6)$$

Here, δ indicates the learning rate and σ indicates the future AW reduction factor. Assume the action denotes the information is transmitted to the PS to NS, the AW is specified to the PS; the action of QV-table for state PS is modified. Though, the PS does not have the QV-table of the NS to modify its QV-table. Furthermore, it is computed at the NS; thus, while the next CH replies accept the information to the sender, it also admits it’s the greatest QV-values and computes the AW. Because the AW is utilized to make a decision on a better solution. This mechanism calculates the AW by PB, PE, PDD, and HC from sender to receiver, and this computation is specified in (7).

$$AW = \gamma^{HC} \times (B + S + PSD) \quad (7)$$

Here, bandwidth (B), speed (S), packet successful delivery (PSD), and hop count (HC). Here, the extra reduction factor is employed to the vehicle award that is necessitated to evade backward. While the NS vehicle's present energy is reasonably great, and the distance between the PS and the NS is small, it minimizes the energy utilization in the network. Reduction factor range between 0 to 1. Figure 4 illustrates the flowchart of the proposed strategy.

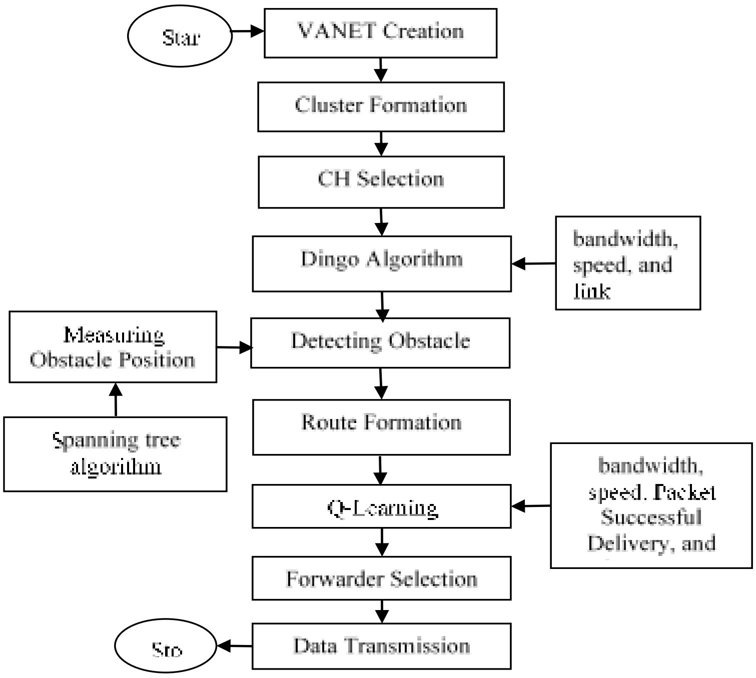

Figure 4. Flowchart of ODQI system

3. SIMULATION ANALYSIS

The described ODQI mechanism is simulated using the network simulator-2 [28]. The VANET simulation region is 1,500×1,500 m^2. The developed ODQI mechanism is evaluated in an urban scenario with vehicles traveling at varying speeds. The vehicle's communication range is 200-500 m, and the vehicle's speed is from 20 to 100 m. ODQI mechanism objective is to increase the lifetime of CHs and provide more stable clustering. We assess CH lifetime, packet successfully delivery ratio (PSDR), packet drop ratio, and delay. PSDR is the ratio of the number of data packets that were successfully transferred from sender vehicles to receiver vehicles to the overall amount of data packets sent. Figure 5 depicts the PDR of HGCM and ODQI mechanisms based on vehicle speed.

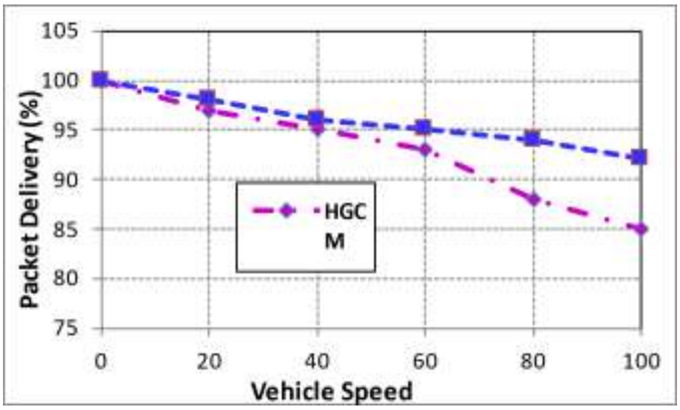

Figure 5. Packet delivery ratio of HGCM and ODQI mechanisms based on vehicle speed

From this figure, when raises the vehicle speed, the HGCM and ODQI mechanisms PDR is increased. Though, the ODQI mechanism has little raises PSDR; because it uses the Q-learning algorithm to select the best forwarder vehicle without dropping the packet in the obstacle present situation. Hence, it reduces the drop rate. Nevertheless, the HGCM mechanisms increase the PSDR when presenting the obstacle. Packet drop rate (PDR) represents the percentage of packets that were sent but not received at their receiver vehicle is known as PDR. Figure 6 explains the PSDR of HGCM and ODQI mechanisms based on vehicle speed.

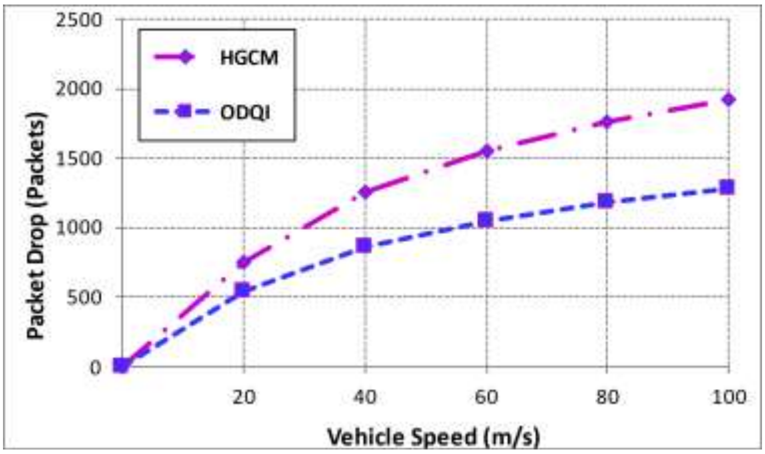

Figure 6. PDR of HGCM and ODQI mechanisms based on vehicle speed

This figure clearly says that when increases the vehicle speed, the PDSR of HGCM and ODQI is minimized. But, the proposed ODQI mechanism has a lesser minimized PDSR since it detects the obstacle and then forwards the traffic information. But, the HGCM mechanism can't able to detect the obstacle efficiently. Delay is the average amount of time that passes between when a packet is delivered by the sender and when it is received by the receiver. The protocol performs better the smaller the value of delay. Figure 7 depicts the delay of HGCM and ODQI mechanisms based on vehicle speed.

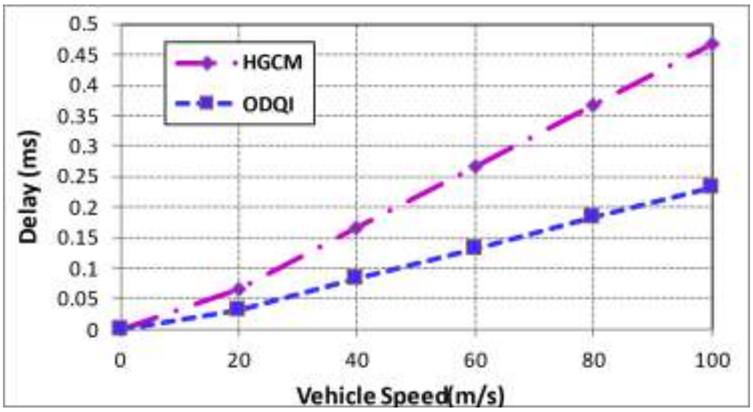

Figure 7. Delay of HGCM and ODQI mechanisms based on vehicle speed

Figure 7 obviously states that when raises the vehicle speed, the HGCM and ODQI mechanisms delay is also raised. The proposed ODQI mechanism uses the spanning tree algorithm to detect the obstacle, and as a result, it evades an extra delay. But, the HGCM mechanism can't detect the obstacle; thus, it increases the delay due to data packet retransmission. Figure 8 demonstrates the lifetime of HGCM and ODQI mechanisms based on DSRC.

The proposed ODQI mechanism selects the CH by applying the dingo algorithm. This algorithm discovers the best CH based on bandwidth, link lifespan, and speed; as a result, it provides a longer CH lifetime and minimizes the possibility of the CH leaving. But, the HGCM mechanism minimizes the CH lifetime. Figure 9 demonstrates the delay of HGCM and ODQI mechanisms based on DSRC.

The DSRC value increases, the delay also increases. The ODQI mechanism compared to the HGCM, the proposed ODQI mechanism has a lesser delay. Since the ODQI mechanism detects the obstacle efficiently and Q-learning chooses the best forwarder based on vehicle PSDR, bandwidth, and speed. As a result, minimizes the delay and increases the routing efficiency.

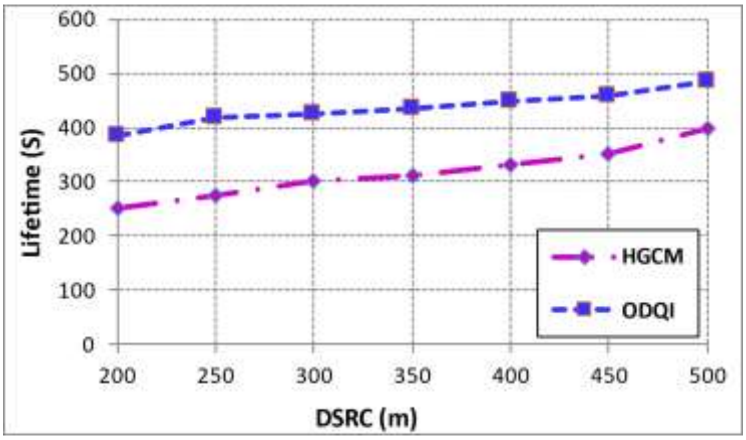

Figure 8. Lifetime of HGCM and ODQI mechanisms based on DSRC

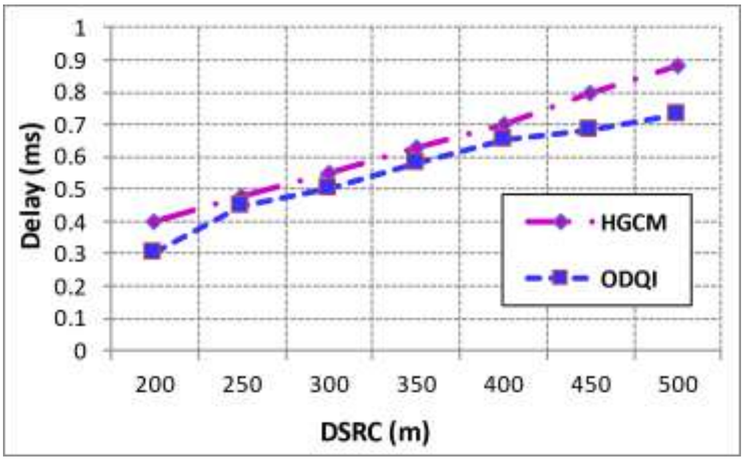

Figure 9. Delay of HGCM and ODQI mechanisms based on DSRC

4. CONCLUSION

In VANET, the link life is affected through the movement of nodes is a significant element in discovering stable routes. Several routing protocols do not concentrate on this element, leading to consecutive route failures, which raises packet losses. However, the majority of clustering techniques move violently with poor data handling, local cluster optimum, and network quality of service (QoS) requirements. This article presents obstacle detection to minimize delay and Q-learning to improve routing efficiency. The spanning tree algorithm detects the obstacle efficiently. This mechanism chooses the best CH by applying the dingo algorithm based on vehicle bandwidth, vehicle speed, and link lifespan. Furthermore, we utilized the Q-learning algorithm to select the forwarder; thus, it provides guarantee and reliable communication in VANETs. The simulation results using the network simulator-2 tool demonstrate that the proposed method improves network PSD ratio, lifetime, and minimizes the routing delay and packet drop ratio.

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