Delay-Minimization and Back-Off Aware Q-Learning with Advanced Bio-Inspired CH Selection for Multi-hop Communication in Vehicular Ad-hoc Networks

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Abstract- The increasing significance of Vehicular Ad-hoc Networks (VANETs) in intelligent transportation systems has introduced challenges related to high mobility, network congestion, and energy efficiency. To address these challenges, this paper proposes a new approach based on Delay-Minimization and Back-Off Aware Q-Learning with Advanced Bio-Inspired Cluster Head (CH) Selection (DBACH) to enhance multi-hop data transmission in VANETs. The DBACH framework is structured around network construction, delay minimization, a back-off Q-learning model, and an improved dragonfly algorithm-based CH selection process. By integrating these mechanisms, the proposed approach effectively minimizes transmission delay, routing overhead, and power consumption, thereby improving Quality of Service (QoS) in VANETs. To validate the performance of DBACH, extensive experiments were conducted, comparing it with existing approaches such as RCDC, DCPA, and WCAM. The simulations were carried out by varying the number of vehicles and their speeds (km/h), analyzing key performance metrics such as energy efficiency, throughput, packet delivery ratio, data loss ratio, computational time, and routing overhead. The results demonstrate that DBACH achieves significant performance gains, with energy efficiency reaching 85 joules, throughput improving to 160–200 Kbps, and an 11–13% increase in packet delivery ratio. Additionally, end-to-end delay is reduced to 60–94 ms, data loss is minimized to 7–15%, and routing overhead is maintained within 170–300 packets. These improvements affirm that DBACH provides high efficiency, greater communication stability, and superior success rates compared to existing methods, making it a promising solution for enhancing reliable and energy-efficient communication in VANETs.

Index Terms: Vehicular Ad-hoc Network (VANET), Delay-Minimization, Multi-hop Communication, Improved Dragonfly Algorithm, CH Selection.

I. Introduction

Vehicular Ad-hoc Networks (VANETs) have emerged as a promising technology within Intelligent Transport Systems (ITS), offering real-time communication solutions for road safety, traffic management, and autonomous vehicle systems. As a specialized subset of Mobile Ad-hoc Networks (MANETs), VANETs enable infrastructure-less communication, where vehicles dynamically exchange information while in motion. These networks facilitate Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Device-to-Device (D2D) communication, ensuring efficient data transmission across road networks. Fig. 1 illustrates the fundamental structure of VANET communication, depicting V2V interactions for cooperative driving and collision avoidance, along with V2I communication, which provides access to traffic information, navigation support, and emergency alerts through roadside infrastructure [1].

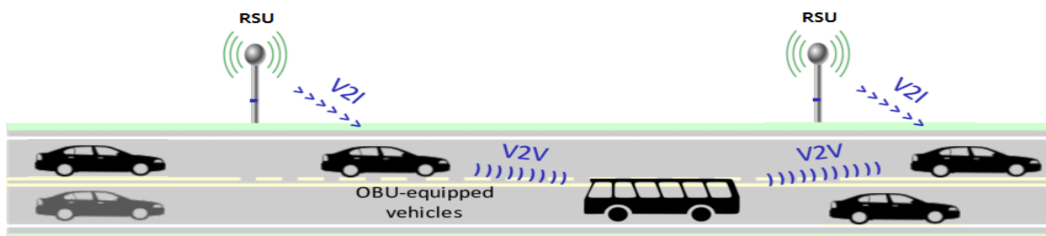

Fig. 1 – Vehicle-based Communication Proces (diagram adapted from Ref. [1]).

To support these communication modes, VANETs rely on Dedicated Short-Range Communication (DSRC) and multi-hop routing protocols to establish stable and reliable links between vehicles. However, high mobility, frequent topology changes, and unpredictable traffic conditions significantly impact network stability and performance. One of the primary challenges in VANETs is ensuring efficient routing while minimizing delay, overhead, and power consumption. Due to the dynamic nature of vehicular movement, frequent disconnections, increased network overhead, and link failures adversely affect packet delivery ratio, throughput, and overall network stability. VANETs employ both centralized and distributed routing models to facilitate data transmission. While centralized routing follows predefined data transmission paths, distributed routing dynamically adapts to real-time network conditions [2]. Research suggests that distributed routing is more efficient in managing high-speed mobility and reducing latency. However, the complexity of multi-hop communication introduces network overhead, leading to increased transmission delays and decreased reliability in real-time applications.

To address these challenges, achieving high Quality of Service (QoS) in VANETs requires advanced clustering techniques, optimized routing models, and delay minimization mechanisms. The IEEE 802.11p/bd standard is commonly used for VANET communication, yet improving network QoS remains an ongoing research focus [3]. In response to these challenges, this paper proposes the Delay-Minimization and Back-Off Aware Q-Learning with Advanced Bio-Inspired CH Selection (DBACH) approach, designed to enhance multi-hop communication efficiency in VANETs. The DBACH framework integrates three key techniques to optimize routing and minimize network congestion: (i) delay minimization strategies, (ii) a Q-learning based back-off model, and (iii) an improved Dragonfly Algorithm (DA) for Cluster Head (CH) selection.

This paper introduces a new approach based on DBACH to improve network performance and ensure efficient data exchange. First, it focuses on reducing network delay, minimizing overhead, and optimizing power consumption by incorporating single-hop and multi-hop communication mechanisms. Second, a Q-learning based back-off model dynamically adjusts contention window sizes, reducing network waiting times and improving transmission efficiency. Lastly, the approach leverages an enhanced Dragonfly Algorithm (DA) for CH selection, ensuring energy-efficient routing and optimal data transmission paths, thereby improving network scalability and reliability [4].

The structure of this paper is as follows: Section II presents an overview of existing clustering and delay minimization methods, highlighting their limitations. Section III introduces the DBACH approach, detailing its network architecture, clustering mechanism, and optimization techniques. Section IV discusses the implementation and performance evaluation of DBACH, comparing its efficiency with existing RCDC-VANETs, DCPA-VANETs, and WCAM-VANETs. Finally, Section V provides the conclusion and future research directions, outlining potential advancements in vehicular network performance and real-world applications.

II. Related Works

Several researchers have explored various techniques to enhance vehicular ad-hoc networks (VANETs) by addressing challenges such as congestion, interference, connectivity, clustering, and routing optimization. This section reviews prior studies on clustering algorithms, routing mechanisms, congestion control, and energy efficiency strategies in VANETs, highlighting their contributions and limitations.

Sewalkar et al. [6] developed the Multi-channel Clustering-based Congestion Control (MC-COCO4V2P) algorithm, which aims to prevent collisions between vehicles and pedestrians while incorporating a transmit power mechanism to optimize energy consumption. While this method effectively reduces power consumption, it provides moderate throughput and packet delivery ratio. Singh et al. [7] proposed a dual-slot transmission method to suppress intra-cluster interference and improve V2V connectivity. Additionally, a graph-based algorithm was introduced for periodic packet transmission, but the method suffers from high energy consumption. Another technique [8] utilized k-means clustering to determine optimal roadside unit (RSU) placement for autonomous vehicles, resulting in enhanced connectivity, cost reduction, and minimal coverage gaps. However, network scalability limitations remain an issue.

In urban VANET environments, Cheng et al. [9] introduced a connectivity prediction-based cluster formation model using geographic routing and multi-layer perceptrons. While this approach achieves low prediction error rates, it suffers from limited network coverage. To optimize cluster size, Shahen et al. [10] developed the Cluster-Based Medium Access Control (CB-MAC) protocol, leveraging a Markov chain model for throughput optimization. Although this method enhances network performance, it is energy-intensive. Another study [11] introduced the VC-attention model, which predicts vehicle interaction behavior using self-attention mechanisms. It identifies key driving features such as DRAC and lane gaps and employs a sliding window for behavior analysis, achieving 92% accuracy on the NGSIM dataset.

In vision-based vehicular communication, a machine learning approach [12] was introduced for autonomous vehicles, involving image pre-processing, feature extraction using PCA, and classification algorithms. This technique significantly enhances obstacle detection and traffic light recognition, improving road safety. Alsarhan et al. [13] developed a fuzzy logic-based clustering control method, integrating multi-criteria decision-making (MCDM) for Cluster Head (CH) selection, ensuring high network stability despite high energy consumption. Similarly, Bi et al. [14] proposed an Affinity Propagation (AP) clustering algorithm, incorporating a weighted mechanism to enhance cluster stability. While this approach improves throughput and packet delivery ratio, it has a complex computational process.

Banikhalaf et al. [15] introduced an Efficient Cluster Head Selection (ECHS) method to optimize network resources, ensuring even cluster distribution and adjusted inter-cluster distances. Despite its efficiency in throughput, lifetime, and packet delivery, the method incurs high power consumption and transmission costs. Khalid et al. [16] proposed a clustering-based routing protocol using a modified k-means algorithm, along with Maximum Stable Set Problem (MSSP) and Continuous Hopfield Network (CHN) for optimization. This method achieves high stability in dense networks and better packet delivery ratios, but suffers from high computational costs.

To enhance network stability and efficient routing, Saad et al. [17] developed the Center-Based Evolving Clustering with Grid Partitioning (CEC-GP) method, ensuring optimized cluster selection. However, the method encounters high packet loss and latency issues. Another approach [18] in Wireless Sensor Networks (WSNs) focused on energy efficiency and data collection by employing mobile data collectors to reduce interference and retransmission overhead, resulting in improved network reliability. Singh et al. [19] proposed the Diverted Path Approach (DPA) for V2V and V2I connectivity, incorporating backup links for reliability, but the method is computationally complex.

Raghavendra et al. [20] developed the Regional Super Cluster-Based Optimum Channel Selection (RSCOC) protocol, which determines the most appropriate communication channel for different regions. This technique achieves high throughput and packet delivery ratios but has high energy consumption. Fakhar et al. [21] analyzed a resource management strategy for V2X networks, focusing on throughput, packet delivery, and latency constraints, though network coverage limitations persist. Weijing et al. [22] proposed the Traffic Differentiated Clustering Routing (TDCR) mechanism in an SDN-enabled hybrid vehicular network, employing an optimization algorithm to balance bandwidth cost and end-to-end delay, but it consumes high power.

Rivoirard et al. [23] introduced the Chain Branch-Leaf (CBL) approach, aimed at increasing broadcast traffic in routing protocols. While this method enhances network stability, it decreases overall throughput. Another study [24] explored the Dragonfly Algorithm (DA) in LEACH-C clustering, optimizing energy consumption while incurring high computational costs. Devarakonda et al. [25] further refined DA-based optimization with a modified convergence and fitness function, improving network lifetime, though complexity remains an issue.

Other techniques focused on improving signal processing and interference reduction. Xueting et al. [26] proposed a multi-packet detection technique using frequency-domain equalization, incorporating successive interference cancellation, which improves V2V and V2I communication reliability. Abdelaziz et al. [27] applied the Dragonfly Algorithm (DA) to the Traveling Salesman Problem (TSP), addressing feature selection, power flow problems, and image segmentation, yet suffering from high energy consumption. Nashaat et al. [28] introduced a novel resource allocation method based on the Dragon meta-heuristic technique, achieving high energy efficiency with moderate throughput and packet delivery ratio. Finally, Xueting et al. [29] proposed the Hybrid Improved Dragon Algorithm (HIDA), which integrates mRMR and IDA for feature selection, increasing classification accuracy at the expense of high power consumption.

The earlier research efforts provided significant contributions in clustering, routing, congestion control, and energy efficiency in VANETs. However, key challenges remain, including high energy consumption, increased packet loss, computational complexity, and routing overhead. These issues impact QoS and network performance, necessitating more efficient, scalable, and adaptive routing mechanisms. Table 1 summarizes these research findings, highlighting their strengths and limitations.

Table 1 – Previous Research Reported in Literature

Ref.	Methodology Details	Advantages	Limitations
[6]	Multi-channel Clustering-based Congestion Control (MC-COCO4V2P) algorithm	Low energy consumption	The throughput and packet delivery ratio is moderate
[7]	Dual-slot transmission method for suppressing intra-cluster interference	Improves the connection between V2V	High energy consumption
[8]	K-means clustering for optimal RUS in self-driving and semi-self-driving cars.	Reduces cost, bandwidth usage	High complexity.
[9]	Connectivity prediction-based cluster formation	Lower error rate	Network coverage is limited
[10]	Cluster-based medium access control (CB-MAC)	Enhances the throughput	High energy consumption
[11]	VC-Attention model using self-attention encoder on a five-vehicle cluster structure	Enhances the lifetime of the network	More computational time.
[12]	Vision-based object recognition using PCA and ML classifiers	Improves road safety and driving efficiency	High processing power
[13]	Fuzzy logic-based clustering control method	High stability and reliability	High energy consumption
[14]	Affinity Propagation (AP) clustering Algorithm	Efficient Throughput, packet delivery	Computational process is complexity
[15]	Efficient Cluster Head Selection (ECHS) method	Efficient throughput, lifetime, packet delivery	Transmission cost is high
[16]	New clustering-based routing protocol with modified K-Means algorithm	Prevent security problems	Computational cost is high
[17]	Center-based evolving clustering based on grid partitioning (CEC-GP) method	Efficient and stable routing	High packet loss with delay
[18]	Optimizing data collection in WSNs, integrating mobile collectors.	Reduces energy depletion in sensor nodes.	High overhead for optimization.
[19]	Diverted Path approach (DPA)	High stability and reliability	A computational process is complex
[20]	Regional Super Cluster-based Optimum Channel Selection (RSCOC)	Delay optimal with low energy consumption high packet delivery ratio, throughput	High energy consumption
[21]	Resource management strategy based on efficient clusters	Better throughput	Minimum coverage area
[22]	Traffic Differentiated Clustering Routing (TDCR) mechanism	Efficiency and service delay	High power consumption
[23]	Chain branch-leaf (CBL)	Stability of the network	Moderate throughput and packet delivery
[24]	Dragon fly algorithm	Minimum energy consumption	Computational cost is high
[25]	Modified dragonfly algorithm (DA)	Enhances the network's lifetime	The computation process is a complexity
[26]	Multipacket detection (MPD) with frequency domain equalization IFDE) and interference cancellation (IC).	Reduces interference and improves V2V and V2I	High complexity in implementation.
[27]	Dynamic resource management is a meta-heuristic algorithm, named Dragonfly Algorithm (DA)	Enhances the network's lifetime	High power consumption
[28]	Dragon meta-heuristic technique	High energy efficiency	Moderate throughput and packet delivery
[29]	Hybrid improved dragon algorithm (HIDA)	Increase the rate of categorization accuracy	High energy consumption

III. Proposed DBACH Approach

The proposed approach is designed to minimize delay and reduce energy consumption in vehicular networks. The key components of this research include VANET network construction, delay optimization using both single-hop and multi-hop communication, a back-off Q-learning model for adaptive contention window adjustment, and an improved Dragonfly Algorithm for efficient CH selection. These elements work together to enhance network stability, optimize data transmission, and improve overall communication efficiency in VANETs.

The workflow of the proposed DBACH approach for VANETs, shown in Fig. 2, follows a structured workflow consisting of three key components: network establishment, latency minimization, and CH selection, all aimed at enhancing network performance, reducing delay, and optimizing resource utilization. The network establishment phase initiates the formation of the vehicular network by dynamically grouping vehicles into clusters. Each cluster is managed by a CH, which serves as a relay node for intra-cluster and inter-cluster communication. The formation of clusters is facilitated through single-hop communication, where vehicles periodically broadcast their mobility, energy status, and connectivity degree. CH selection in this phase is based on parameters such as energy availability, mobility, and link stability to ensure efficient communication. VANETs operate in both V2V and V2I modes, and the DBACH framework dynamically adapts to the most efficient communication mode depending on network conditions.

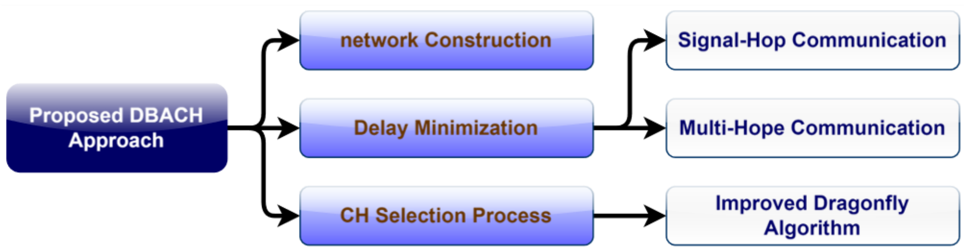

Fig. 2 – Workflow of the Proposed DBACH Approach.

To minimize latency, the DBACH approach incorporates multi-hop communication, which allows packets to be relayed through multiple intermediate vehicles instead of relying solely on direct transmission to CHs or roadside units. This is particularly effective in dynamic environments where direct communication may be hindered by network topology changes. The Q-learning based back-off model further enhances delay minimization by dynamically adjusting the contention window (CW) size based on real-time network conditions, thereby preventing congestion and reducing unnecessary retransmissions. Additionally, a priority-based packet forwarding mechanism ensures that critical messages, such as emergency alerts, receive precedence, thereby improving response times and overall network efficiency.

A crucial aspect of DBACH is its optimized CH selection, which is achieved using an enhanced Dragonfly Algorithm (DA). The DA is a bio-inspired optimization technique that mimics the behavior of dragonflies in their natural environment. It employs five key behaviors—separation, alignment, cohesion, attraction, and distraction—to identify the most suitable CHs based on various network parameters. The fitness function used in CH selection prioritizes vehicles with higher residual energy, lower transmission distance, and stronger network connectivity to maximize network stability and prolong CH lifespan. To further optimize resource utilization, DBACH integrates an adaptive CH rotation mechanism, which periodically re-elects CHs based on energy consumption trends, ensuring even distribution of network load and preventing premature node depletion.

The overall workflow of DBACH ensures a high level of network efficiency by integrating these three components into a seamless framework. The network establishment phase sets up stable clusters, the latency minimization phase optimizes data transmission through multi-hop relaying and adaptive contention window adjustments, and the CH selection phase guarantees optimal energy efficiency and clustering stability through Dragonfly Algorithm-based CH selection. By combining these techniques, the DBACH approach enhances packet delivery ratio, reduces end-to-end delay, optimizes power utilization, and minimizes routing overhead, significantly improving the QoS in VANETs. The proposed approach proves particularly beneficial for Intelligent Transport Systems (ITS), smart traffic management, autonomous vehicles, and emergency communication networks, where real-time data exchange is critical.

A. VANETs Network Construction

The heterogeneous clustering-based DBACH network model, illustrated in Fig. 3, consists of Cluster Heads (CHs) and Cluster Children (CCs), where CHs serve as service providers, facilitating both intra-cluster and inter-cluster communication among vehicles on a roadway. Dedicated Short-Range Communication (DSRC) links operate over a single communication channel to enable data transmission between vehicles. To further improve communication efficiency and reduce data collisions, Visible Light Communication (VLC) links are incorporated into vehicles using light-emitting diodes (LEDs) and photodiodes (PDs), allowing for multi-channel data transmission among neighboring vehicles. Within a cluster, communication between CHs and CCs occurs through two methods: first, via single-hop DSRC-based direct communication, and second, via multi-hop transmission through neighboring vehicles using VLC links.

Communication between the source and destination is designed to occur within milliseconds (ms), ensuring real-time, low-latency data transmission. To manage packet transfers efficiently and avoid network congestion, the DBACH network utilizes the IEEE 802.11p MAC protocol, which incorporates the Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) mechanism. As illustrated in Fig. 3, CHs are represented in red, while CCs are shown in orange, visually distinguishing their roles within the network. The DBACH model enhances scalability, improves energy efficiency, and ensures reliable data delivery, making it a robust solution for vehicular ad hoc networks (VANETs).

Fig. 3 was derived through a simulation-based design approach, where the DBACH network topology was structured to incorporate heterogeneous clustering, dynamic CH selection, and hybrid communication mechanisms. The network layout was developed to support single-hop DSRC for direct communication and multi-hop VLC for extended connectivity among vehicles. The CH selection process was optimized using the Dragonfly Algorithm, ensuring balanced energy consumption, stable connectivity, and reduced transmission delays. The final visualization in Fig. 3 was generated based on simulated node placement, clustering algorithms, and communication link formations, effectively illustrating the role of CHs in managing network traffic and enhancing the overall QoS in VANETs.

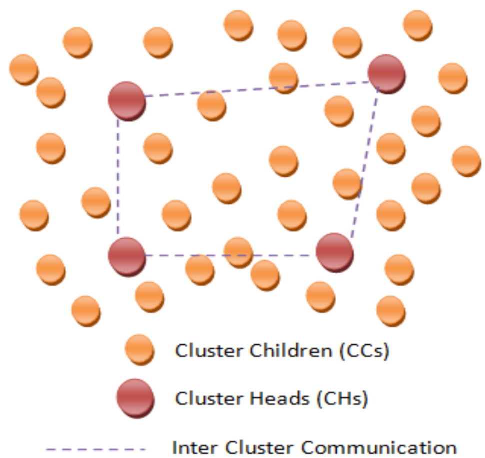

Fig. 3 – Proposed DBACH Network Model.

B. Delay Minimization

In vehicular networks, high mobility often complicates data transmission, leading to increased communication delays. To address this challenge, it is crucial to implement effective delay minimization strategies. The proposed network model supports both single-hop and multi-hop communication among heterogeneous vehicles, ensuring efficient data exchange. By optimizing single-hop and multi-hop transmission mechanisms, the model effectively reduces the average delay between CH and CC, thereby enhancing network responsiveness and overall communication efficiency. The CC vs in the network is represented as $\Omega = \{cc_1, cc_2 \ldots\}$ where v_{ch} is represented as the CH. Thus all the CC vehicles $\Omega_{ch} = \Omega \backslash v_{ch}$ where Ω_{single} *and* Ω_{multi} represents the single and the multi-transmission and the transmission between the CH and CC of any vehicles v_i and v_{ch} is represented as $T_{i,ch}$, where $v_i \in \Omega_{ch}$.

1) *Single-Hop Communication*

In single-hop communication, CC vehicles transmit data directly to their CH using a Dedicated Short-Range Communication (DSRC) link. The Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) mechanism is integrated to manage data transmission and prevent collisions. To accurately assess the efficiency of single-hop communication, two key factors are measured: propagation delay, which refers to the time taken for data to travel between vehicles, and contention delay, which accounts for the time spent waiting for access to the communication channel. In general the network propagation delay (t_0) is the time taken to send the data packets from one source to the destination and it is mathematically expressed in the equation (1).

$$t_0 = \frac{S_{TP}}{D_{rate}} \tag{1}$$

In equation (1), the terms S_{TP} implies the transmitted packet size and the D_{rate} implies the DSRC link data rate. The other variables that are present in the delay calculations are vehicle probability (VP_i) and channel access (CA_i) and the mathematical expression for the calculation of those variables is given in equation (2) and (3).

$$CA_i = \frac{2VP_i}{CW_s+1} \tag{2}$$

$$VP_i = \prod_{\Omega_{single} \cup v_{ch} \setminus v_i} (1 - CA_i) \tag{3}$$

In equation (3), the terms CW_s implies the contention window size. In the CSMA/CA mechanism, if the threshold of the channel is attained the vehicle will wait for a certain period to initiate the channel again. The average waiting time is mathematically expressed in equation (4).

$$AW_{time} = VP_i * s_{time} + T_s^{tx} \tag{4}$$

In equation (4), the terms s_{time} implies the slot time and the T_s^{tx} implies the threshold transmission time. The term $1/CA_i\,VP_i$ implies the slot time count that the vehicle v_i should wait until the packets are successfully to the destination. The data packet transmission between any two vehicles in Ω_{single} and v_{ch} is the summation of the propagation delay and contention delay and it is mathematically expressed in the equation (5).

$$T_{i,ch} = 1 + \frac{AW_{time}}{CA_i * VP_i} \tag{5}$$

From equation (5) the single-hop transmission delay between the CH and CC is measured using the DSRC link and CSMA/CA mechanism.

2) Multi-Hop Communication

In multi-hop communication, CC vehicles relay data to their CH through adjacent vehicles using a Visible Light Communication (VLC) link. While VLC enables efficient data transmission, its effectiveness is time-limited due to environmental factors and line-of-sight constraints. However, within this operational period, VLC significantly reduces channel contention delay, ensuring faster and more reliable communication between adjacent vehicles. To measure the multi-hop communication delay between the current vehicle (v_i) and its adjacent vehicle (v_j) In the communication link of the VLC link, the propagation delay of the overall transmitted packet is calculated (where contention delay is zero) and it is mathematically expressed in equation (6).

$$t_1 = \frac{S_{TP}}{D_{rate}^{v}} \tag{6}$$

In equation (6), the terms S_{TP} implies the transmitted packet size, and the D_{rate}^{v} implies the VLC data rate between v_i and v_j. The data packet transmission between any two vehicles in Ω_{multi} and v_{ch} is the calculation of the summation of the delay among the vehicles v_j and v_{ch} and propagation delay between v_i and v_j and it is mathematically expressed in the equation (7).

$$T_{i,ch} = \underset{j}{\min}\,(t_{j,ch} + t_1) \tag{7}$$

From equation (7) the multi-hop transmission delay between the CH and CC is measured using the VLC link.

C. Back-Off Model Q-Learning

To enhance communication efficiency in the network, a Q-learning based approach is introduced in this section. This method dynamically adjusts the Contention Window (CW) size based on the level of network collisions, optimizing channel access and reducing transmission delays. Two conditions are applied that is CW-CWmin after each successful transmission and as well CW+CWmin after each collision. Fig. 4 illustrates the process of the back-off Q learning model.

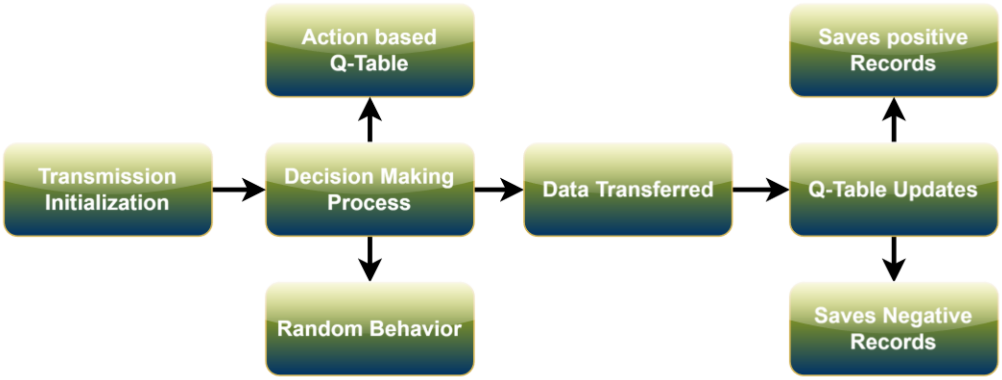

Fig. 4 - Back-off Q-Learning Process.

To analyze Contention Window size variations in a dynamically changing environment, a Q-learning based approach is utilized. This adaptive mechanism adjusts CW size for both inter-cluster and intra-cluster communication, optimizing single-hop and multi-hop transmission to enhance network efficiency and reduce delays. The mathematical expression for the end reward of both these communication models is given in equations (8) and (9).

$$R\Omega_{single} = \frac{\log 2\,(CW1\,m\,in+1)}{\log 2\,(CW1\,current+1)} \tag{8}$$

$$R\Omega_{multi} = \frac{\log 2\,(CW1\,m\,in+1)}{\log 2\,(CW1\,current+1)} * \frac{\log 2\,(CW2\,m\,in+1)}{\log 2\,(CW2\,current+1)} \tag{9}$$

From the equation (8) and (9) the learning is performed and the CW size is measured for the inter-cluster and intra-cluster communication in the dynamically varying VANET environment.

D. Improved Dragonfly Algorithm-based CH Selection Process

1) Dragonfly Algorithm Background

The Dragonfly Algorithm (DA) is a meta-heuristic optimization algorithm inspired by Swarm Intelligence (SI). It is modeled after the hunting and migratory behaviors of dragonflies, incorporating both static and dynamic behaviors to enhance the search for optimal solutions.

In its static behavior, DA estimates the global optimum, enabling an efficient search mechanism to identify the best solutions within a given neighborhood. Meanwhile, in its dynamic behavior, a large number of dragonflies form groups and migrate collectively to avoid predators, simulating adaptive decision-making in optimization problems.

The algorithm operates based on five fundamental principles: separation (avoiding overcrowding), alignment (maintaining direction within the swarm), cohesion (ensuring group stability), attraction towards food (searching for optimal solutions), and distraction from enemies (escaping suboptimal conditions). These key operations, which define the functionality of DA, are illustrated in Fig. 5.

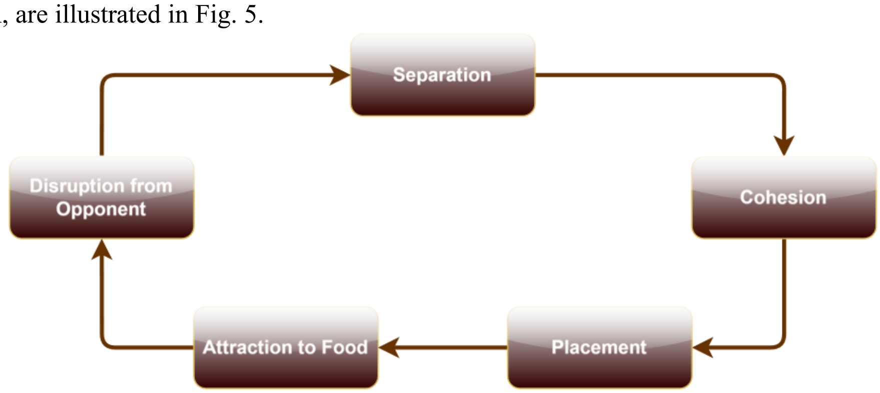

Fig. 5 – Operations of Dragonflies.

2) *Hierarchical Clustering*

Clustering plays a crucial role in enhancing the network lifetime in VANETs. Due to the highly dynamic nature of VANETs, it is essential to optimize the clustering process to ensure efficient and stable communication.

At the initial stage, CH selection is performed using the LEACH-C algorithm, where the primary selection criterion is the remaining energy of each vehicle. The vehicle with the highest residual energy is initially chosen as the CH. However, to further optimize CH selection, the DA is applied, incorporating additional parameters such as energy, distance, and algorithm-specific factors. The fitness value of each CH is then calculated, and the vehicle with the best fitness (lowest value) is selected as the optimal CH.

Once the CHs are determined, their coverage area is measured, and vehicles within this range become CC. In the network, both inter-cluster and intra-cluster communication take place to facilitate data exchange efficiently. The five fundamental operations of the DA algorithm—separation, cohesion, alignment, attraction, and distraction from enemies—are utilized to optimize clustering and routing. The mathematical expressions defining these operations are provided in Table 2 and Table 3.

Table 2 – Operations and Expressions

Operations	Expressions
Separation Operation	$SO(s_1,i) = -\sum_{s=1}^{N} A(s_1,i) - A(s_2,i)$
Alignment Operation	$AO(s_1,i) = \frac{\sum_{s_2=1}^{N} V(s_2,i)}{N}$
Cohesion Operation	$CO(s_1,i) = \frac{\sum_{s_2=1}^{N} x(s_2,i)}{N} - A(s_1,i)$
Food Attraction	$FA(s_1,i) = A^+ - A(s_1,i)$
Distraction of Enemies	$ED(s_1,i) = A^- + A(s_1,i)$

Table 3 – Terms and Definitions

Operations	Expressions
$SO(s_1,i)$	Separation operation
$A(s_1,i)$	Location of the current solution and its iteration
$A(s_2,i)$	Location of the neighbor solution and its iteration
N	Neighbor solution count
$AO(s_1,i)$	Alignment operation
$V(s_2,i)$	Velocity of neighbor solution
$CO(s_1,i)$	Cohesion operation
$FA(s_1,i)$	Food attraction operation
A^+	Location of the food
$ED(s_1,i)$	Distraction of enemies

Using the Table 2 and 3 the movement of the dragonflies towards a particular direction is measured and it is mathematically expressed by:

$$\Delta A_{t+1} = \left(sSO(s_1,i) + aAO(s_1,i) + cCO(s_1,i) + fFA(s_1,i) + eED(s_1,i)\right) + w\Delta A_t \tag{10}$$

The position vectors are calculated by using the step vectors with the help of the current iteration *t*.

$$A_{t+1} = A_t + \Delta A_{t+1} \tag{11}$$

The dragonfly finds the neighboring position using a random walk to find the solution. Using this evaluation the fitness function is performed with the energy and distance estimations and the mathematical expression for the calculation of energy and distance is given in equations (12) and (13).

$$E(i,j) = \sum_{i=1}^{M} E(v_i) \Big/ \sum_{j=1}^{N} (CH_j) \quad (12)$$

$$D(i,j) = \min \{\textstyle\sum_{k\in j} dis(v_i, CH_j) \big| C_j\} \quad (13)$$

Using equations (12) and (13) the fitness function is measured and it is expressed in equation (14) [30].

$$f = \alpha * E(i,j) + (1-\beta) * D(i,j) \quad (14)$$

Equation (14) shows the fitness function utilized for choosing the optimal CH in the DBACH-VANETs approach. It balances energy efficiency $E(i,j)$ with distance minimization $D(i,j)$ by employing weight factors α and β. Increased energy prolongs network lifespan, whereas shorter distances minimize communication problems. The formula emphasizes CHs according to energy levels and closeness, enhancing clustering and service quality in VANET communications. These calculations help determine the optimal solution for ensuring efficient inter-cluster and intra-cluster communication in the VANET network. By implementing the proposed DBACH-VANETs approach, the overall network performance is significantly enhanced, leading to improved vehicle communication and higher QoS in real-time traffic scenarios.

IV. Simulation Experimentations

To evaluate the performance of the proposed DBACH-VANETs approach in addressing large-scale vehicular network challenges, extensive simulations were conducted. The experiments were performed using Network Simulator 2 (NS2) on a Windows operating system with 8 GB RAM. The analysis considered two key variables: the number of vehicles and varying speeds (km/h).

The performance evaluation was based on several critical metrics, including energy efficiency, throughput, packet delivery ratio, data loss ratio, end-to-end delay, and network overhead. For a comparative analysis, the proposed approach was benchmarked against existing VANET protocols, specifically RCDC-VANETs [30], DCPA-VANETs [31], and WCAM-VANETs [32]. The input parameters used for the simulation and implementation process are detailed in Table 4.

Table 4 – Simulation Settings

Parameters	Values
Simulator	NS2.35
Time	200 ms
Coverage Area	1000m*1000m
No of Vehicles	200 Nodes
Radio Type	IEEE 802.14.2
Antenna Type	Omni-directional Antenna
Mobility Model	Random Waypoint
UMTS Threshold	-94 dBm
Queue Type	DropTail
Node Speed	10Km/hr to 50Km/hr
Initial Power	1000 mJ
Transmission Power	0.500 Joules
Receiving Power	0.050 Joules
Data Rate	250 Kbps
DATA Traffic	CBR
Agent Type	UDP

A. Results concerned with Number of Vehicles

This section presents the simulation results based on the number of vehicles, with graphical comparisons for RCDC-VANETs, DCPA-VANETs, WCAM-VANETs, and DBACH-VANETs. The key performance metrics used in the evaluation include energy efficiency, throughput, packet delivery ratio, data loss ratio, end-to-end delay, and overhead.

1) *Energy Efficiency Calculation*

Energy efficiency measures the remaining energy retained at the end of the simulation, considering a varying number of vehicles. Achieving high energy efficiency is crucial for ensuring reliable and sustainable communication in vehicular networks and IoT applications. Fig. 6 provides a graphical illustration of energy efficiency across different methods, demonstrating that the proposed DBACH-VANETs approach outperforms RCDC-VANETs, DCPA-VANETs, and

WCAM-VANETs. This improvement is attributed to DBACH-VANETs' integration of multi-hop communication and an optimization-based Cluster Head (CH) selection process, which significantly reduces power consumption and enhances network energy efficiency by the end of the simulation.

2) *Throughput Calculation*

Throughput refers to the total number of data packets successfully transmitted, including forwarded packets, across all nodes in the network. Fig. 7 presents a graphical analysis of throughput performance for the compared methods, showing that DBACH-VANETs achieves significantly higher throughput than RCDC-VANETs, DCPA-VANETs, and WCAM-VANETs. The proposed method enhances data transmission efficiency by incorporating delay minimization techniques and enabling optimized single-hop and multi-hop communication. This approach allows a higher volume of data to be transmitted within a defined time frame, improving network utilization and overall communication efficiency among vehicles.

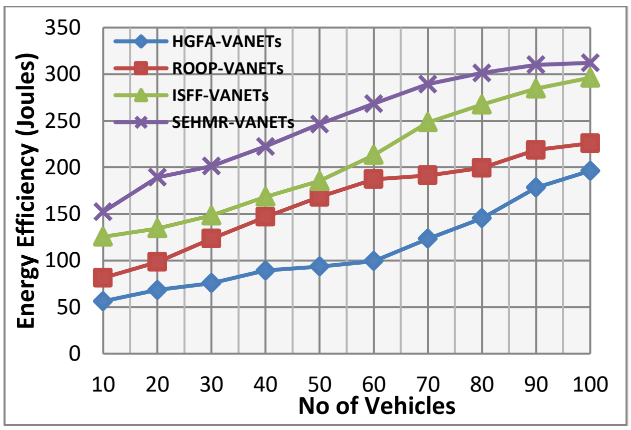

Fig. 6 - Energy Efficiency Calculation.

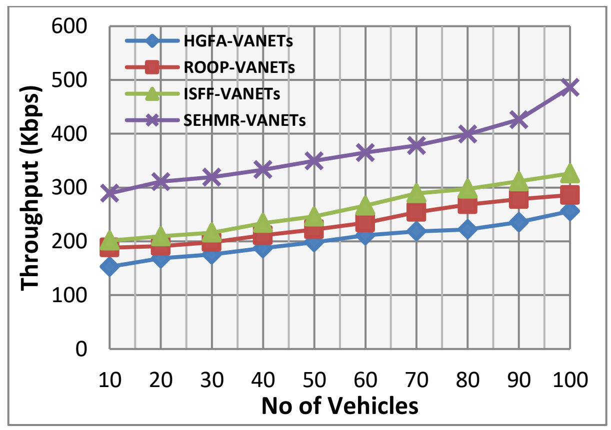

Fig. 7 - Throughput Calculation.

3) Packet Delivery Ratio (PDR) Calculation

Packet Delivery Ratio (PDR) represents the percentage of data packets successfully received at the destination relative to the total packets generated at the source. Fig. 8 provides a graphical representation of PDR performance, demonstrating that the proposed DBACH-VANETs approach achieves higher packet delivery efficiency compared to RCDC-VANETs, DCPA-VANETs, and WCAM-VANETs. The optimization-based clustering process in DBACH-VANETs ensures that data is transmitted through the most efficient path, reducing delay and network overhead. Additionally, the high accuracy of received data at the destination contributes to a significant improvement in the delivery rate, enhancing overall network reliability and QoS.

4) Packet Loss Ratio (PLR) Calculation

Packet Loss Ratio (PLR) measures the percentage of data packets lost during transmission between network nodes. Fig. 9 illustrates the packet loss comparison among the evaluated methods, showing that DBACH-VANETs significantly reduces packet loss compared to RCDC-VANETs, DCPA-VANETs, and WCAM-VANETs. Earlier methods suffer from improper path selection and inefficient power utilization, leading to higher packet loss and reduced QoS. In contrast, DBACH-VANETs incorporates optimization-based clustering, energy-efficient transmission, and a combination of single-hop and multi-hop communication, which collectively enhance delivery reliability and minimize data loss. As a result, DBACH-VANETs achieves significantly lower packet loss, ensuring more stable and efficient data transmission across the network.

5) End-to-End Delay Calculation

End-to-End Delay refers to the total time taken for a node to generate and successfully transmit data packets to their destination. Fig. 10 presents a graphical comparison of end-to-end delay across different methods, showing that DBACH-VANETs achieves significantly lower delay compared to RCDC-VANETs, DCPA-VANETs, and WCAM-VANETs. This improvement is due to the optimized data transmission process in DBACH-VANETs, which ensures that packets travel through the most efficient paths at each instant. By dynamically selecting optimal routing paths, the proposed approach minimizes latency and enhances real-time communication efficiency, leading to better QoS outcomes in vehicular networks.

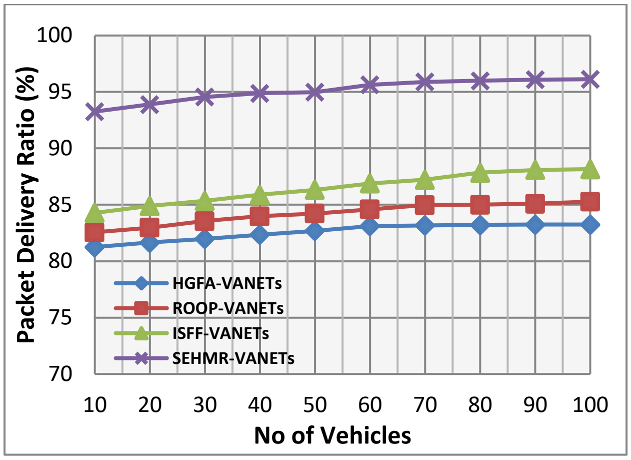

Fig. 8 - Packet Delivery Ratio Calculation.

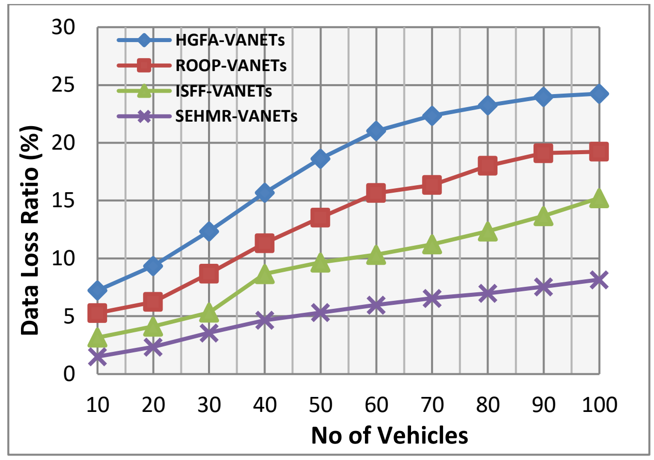

Fig. 9 - Packet Loss Calculation.

6) Routing Overhead Calculation

Routing Overhead is the ratio of total data packets generated at the source to the total packets forwarded across the network. Fig. 11 illustrates the routing overhead comparison, demonstrating that DBACH-VANETs significantly reduces overhead in contrast to RCDC-VANETs, DCPA-VANETs, and WCAM-VANETs. The proposed method efficiently determines the optimal route among multiple possible paths, thereby minimizing unnecessary packet forwarding. By reducing redundant data transmissions, DBACH-VANETs optimizes network resource utilization, leading to lower routing overhead and improved overall efficiency in vehicular communication.

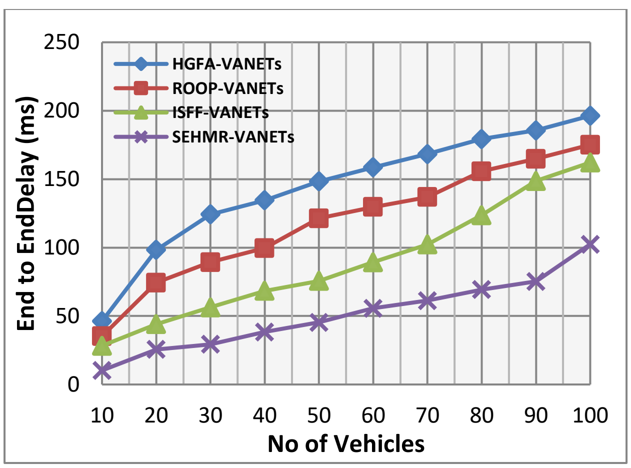

Fig. 10 - End-to-End Delay Calculation.

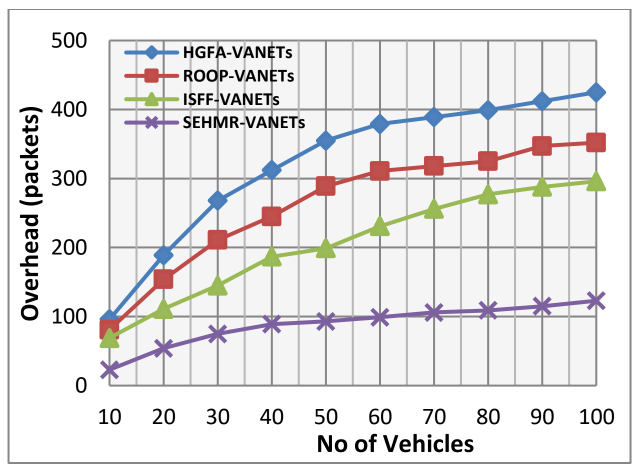

Fig. 11 - Routing Overhead Calculation.

B. Results and Discussion concerned with Number of Vehicles

This section presents a detailed discussion of the simulation results, focusing on the impact of vehicle count on network performance. The analysis compares the proposed DBACH-VANETs approach with earlier methods to evaluate improvements in energy efficiency, throughput, packet delivery ratio, data loss ratio, end-to-end delay, and overhead. The performance measurements for these parameters are illustrated in Tables 5 and 6, providing a comprehensive comparison of the effectiveness of the proposed approach against existing techniques.

Table 5 – Measurement of the parameters such as energy efficiency, throughput, and packet delivery ratio concerned with number of vehicles

No of Vehicles	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs
	Energy Efficiency (Joules)				Throughput (Kbps)				Packet Delivery Ratio (%)			
10	56.28	81.28	125.46	152.23	152.83	188.32	201.32	289.31	81.25	82.56	84.28	93.26
20	68.31	98.31	134.32	189.31	168.32	191.23	209.32	311.02	81.65	82.98	84.89	93.89
30	75.66	123.31	148.31	201.32	175.65	198.36	216.35	319.32	81.98	83.56	85.35	94.56
40	89.32	146.78	168.33	222.35	187.36	211.35	234.16	333.31	82.35	83.98	85.89	94.89
50	93.54	168.11	185.33	246.35	198.31	222.12	246.38	349.65	82.69	84.23	86.32	94.99
60	99.31	187.21	213.33	268.38	211.32	234.65	266.38	365.15	83.12	84.59	86.89	95.64
70	123.35	191.23	248.33	289.34	218.65	254.25	289.34	378.21	83.18	84.97	87.22	95.89
80	145.31	199.35	267.34	301.32	222.32	268.65	297.65	399.34	83.21	85.01	87.84	95.99
90	178.35	218.65	284.55	310.02	235.48	278.49	311.56	426.35	83.24	85.09	88.08	96.09
100	196.28	225.79	296.17	312.17	256.17	286.17	326.17	486.17	83.25	85.28	88.16	96.13

The energy efficiency of the proposed SEHMR-VANETS approach is 312.17 Joules, which is significantly higher than the earlier methods. Specifically, HGFA-VANETS, ROOP-VANETS, and ISFF-VANETS achieve 196.28 Joules, 225.79 Joules, and 296.17 Joules, respectively. This indicates that the proposed SEHMR-VANETS approach improves energy efficiency by 16 Joules over ISFF-VANETS, 86.38 Joules over ROOP-VANETS, and 115.89 Joules over HGFA-VANETS.

The throughput of SEHMR-VANETS is 486.17 Kbps, whereas HGFA-VANETS, ROOP-VANETS, and ISFF-VANETS achieve 256.17 Kbps, 286.17 Kbps, and 326.17 Kbps, respectively. This means that SEHMR-VANETS outperforms ISFF-VANETS by 160 Kbps, ROOP-VANETS by 200 Kbps, and HGFA-VANETS by 230 Kbps, demonstrating a significant improvement in data transmission rates.

The packet delivery ratio (PDR) of SEHMR-VANETS is 96.13%, compared to 83.25% for HGFA-VANETS, 85.28% for ROOP-VANETS, and 88.16% for ISFF-VANETS. This results in an 8% improvement over ISFF-VANETS, 11% over ROOP-VANETS, and 13% over HGFA-VANETS, highlighting the enhanced reliability and data transmission success rate of the proposed approach.

Table 6 – Measurement of the parameters such as data loss ratio, end-to-end delay, and overhead concerned with number of vehicles

No of Vehicles	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs
	End-to-End Delay (ms)				Data Loss Ratio (%)				Overhead (Packets)			
10	46.28	35.23	28.26	10.25	7.23	5.28	3.16	1.51	96	81	69	23
20	98.31	74.32	44.12	25.66	9.35	6.24	4.12	2.35	189	154	111	54
30	124.32	89.31	56.35	29.33	12.35	8.69	5.33	3.56	268	211	145	75
40	134.56	99.64	68.35	38.31	15.68	11.32	8.66	4.66	312	245	187	89
50	148.36	121.31	75.68	45.35	18.64	13.54	9.66	5.33	355	289	199	93
60	158.64	129.65	89.35	55.66	21.03	15.66	10.33	5.98	379	311	231	99
70	168.34	136.89	102.32	61.23	22.35	16.35	11.23	6.56	389	318	256	106
80	179.32	155.68	123.65	69.33	23.25	18.01	12.35	6.98	399	325	277	109
90	185.66	164.88	148.66	75.33	23.98	19.11	13.68	7.55	412	347	288	115
100	196.28	175.13	162.14	102.46	24.25	19.23	15.23	8.17	425	352	296	123

The end-to-end delay of the proposed SEHMR-VANETS approach is 102.46 ms, which is significantly lower than the earlier methods. Specifically, HGFA-VANETS, ROOP-VANETS, and ISFF-VANETS have delays of 196.28 ms, 175.13 ms, and 162.14 ms, respectively. This demonstrates that SEHMR-VANETS reduces end-to-end delay by 60 ms compared to ISFF-VANETS, 73 ms compared to ROOP-VANETS, and 94 ms compared to HGFA-VANETS, ensuring faster and more efficient data transmission.

The data loss rate of SEHMR-VANETS is 8.17%, whereas HGFA-VANETS, ROOP-VANETS, and ISFF-VANETS experience 24.25%, 19.23%, and 15.23% data loss, respectively. This indicates that SEHMR-VANETS achieves a 7% reduction in data loss compared to ISFF-VANETS, 11% reduction compared to ROOP-VANETS, and 15% reduction compared to HGFA-VANETS, enhancing network reliability and packet transmission success rates.

The routing overhead in SEHMR-VANETS is 123 packets, significantly lower than HGFA-VANETS (425 packets), ROOP-VANETS (352 packets), and ISFF-VANETS (296 packets). This results in a reduction of 170 packets compared to

ISFF-VANETS, 220 packets compared to ROOP-VANETS, and 300 packets compared to HGFA-VANETS. The reduced overhead in SEHMR-VANETS demonstrates its efficient routing mechanism, minimizing unnecessary packet forwarding and improving overall network performance.

C. Results concerned with Varying Speed

In this section, the simulation results are analyzed by varying vehicle speeds from 10 km/h to 50 km/h. The performance of the proposed DBACH-VANETs approach is compared against existing methods, including RCDC-VANETs, DCPA-VANETs, and WCAM-VANETs. The key performance metrics evaluated include energy efficiency, throughput, packet delivery ratio, data loss ratio, end-to-end delay, and overhead.

1) Energy Efficiency Calculation

Fig. 11 illustrates the energy efficiency comparison across varying vehicle speeds. The results demonstrate that DBACH-VANETs achieves superior energy efficiency compared to the earlier methods. In conventional approaches, energy consumption tends to increase significantly during high-traffic conditions, negatively impacting network QoS. However, DBACH-VANETs optimizes power utilization by effectively integrating single-hop and multi-hop communication, ensuring that energy is used efficiently in necessary areas. Additionally, the approach selects the shortest and most optimal path for data transmission, even at higher speeds, thereby enhancing QoS during communication.

2) Throughput Calculation

Fig. 12 presents the throughput comparison across different vehicle speeds. The results show that DBACH-VANETs consistently achieves higher throughput than the earlier methods. The improved throughput performance in DBACH-VANETs is attributed to its delay-minimization strategies and efficient data transmission, even in high-speed vehicular environments. As vehicle speed increases, the throughput also improves, supported by multi-hop communication and optimization-based clustering. These mechanisms ensure efficient data flow, reduced congestion, and enhanced network stability, making DBACH-VANETs more effective in high-speed vehicular scenarios.

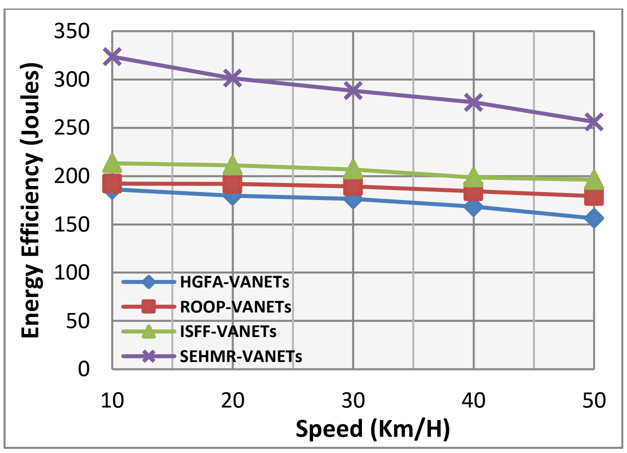

Fig. 11 – Energy Efficiency Calculation.

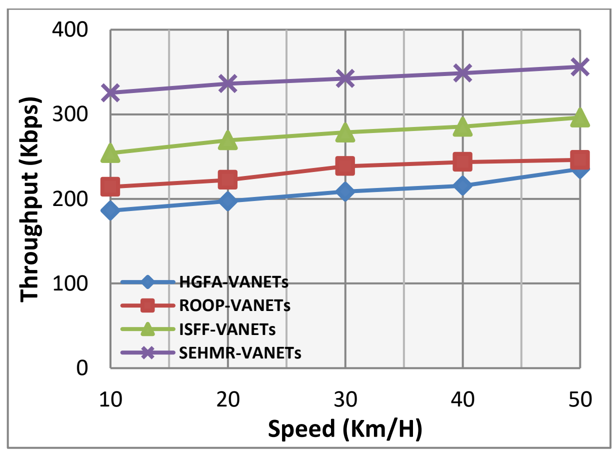

Fig. 12 - Throughput Calculation.

3) Packet Delivery Ratio (PDR) Calculation

Fig. 13 provides a graphical representation of the Packet Delivery Ratio (PDR) across varying speeds from 10 km/h to 50 km/h. The results indicate that the proposed DBACH-VANETs approach consistently outperforms earlier methods. The reduction in communication delay plays a crucial role in enhancing the delivery ratio, ensuring that a higher percentage of transmitted data successfully reaches the destination. While the improvement in PDR is marginal compared to previous methods, DBACH-VANETs achieves a more stable and reliable data transmission rate, contributing to a higher level of communication quality within the vehicular network.

4) Packet Loss Ratio (PLR) Calculation

Fig. 14 illustrates the packet loss ratio across different vehicle speeds, comparing DBACH-VANETs with existing methods. The findings confirm that DBACH-VANETs exhibits lower packet loss than the previously scheduled approaches. As the number of users and vehicle speed increase, the proposed method maintains a lower packet loss rate due to its effective clustering mechanism and optimization-based routing strategy. These enhancements improve data transmission stability, ensuring that fewer packets are lost even under high-speed conditions, ultimately leading to more efficient and reliable communication in VANETs.

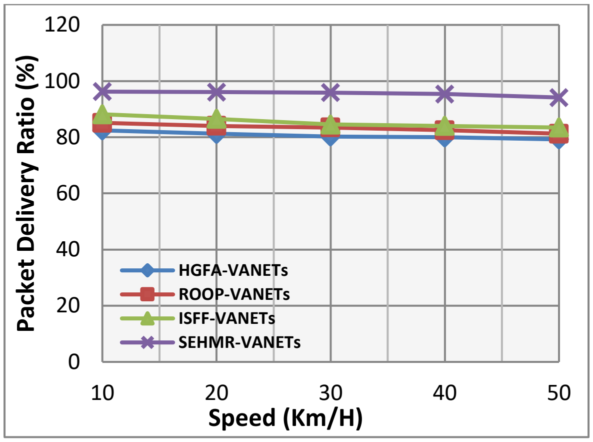

Fig. 13 - Packet Delivery Ratio Calculation.

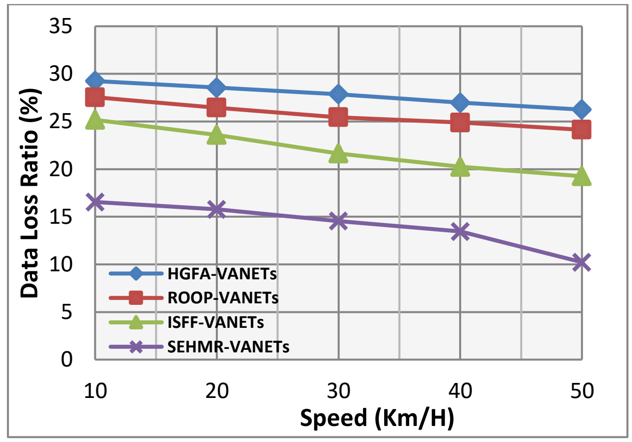

Fig. 14 - Packet Loss Calculation.

5) End-to-End Delay Calculation

Fig. 15 presents the end-to-end delay comparison across varying speeds from 10 km/h to 50 km/h. The results confirm that the proposed DBACH-VANETs approach significantly reduces delay compared to earlier methods. This improvement is achieved through the effective optimization-based clustering process, which minimizes transmission delays by ensuring efficient routing and data forwarding mechanisms. While the reduction in delay is gradual, it plays a crucial role in enhancing real-time communication efficiency in VANETs.

6) Routing Overhead Calculation

Fig. 16 illustrates the routing overhead comparison at different vehicle speeds. The findings demonstrate that DBACH-VANETs achieves lower routing overhead than previous approaches. Managing routing overhead at higher speeds is a challenging task, as increasing speed often leads to frequent route disruptions and excessive data forwarding. However, DBACH-VANETs effectively addresses this challenge by utilizing optimized Cluster Head selection and an optimal path selection process, which reduces unnecessary data transmissions. As a result, the proposed method maintains efficient data forwarding, ultimately leading to improved QoS and network stability during high-speed communication.

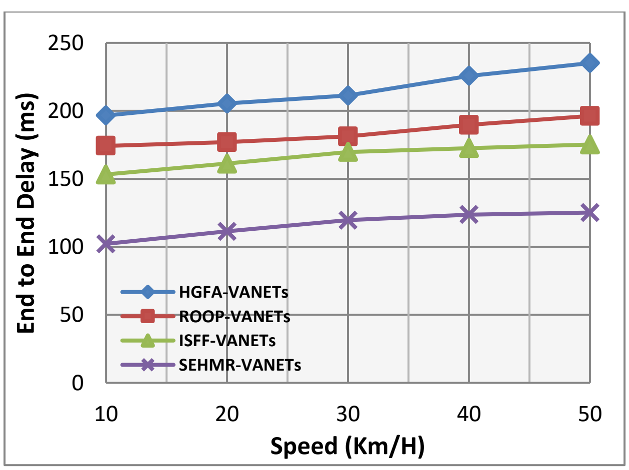

Fig. 15 - End-to-End Delay Calculation.

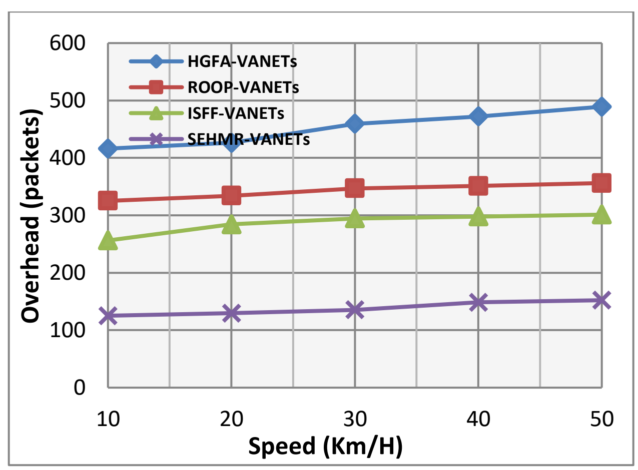

Fig. 16 - Routing Overhead Calculation.

D. Results and Discussion Concerned with Varying Speed

This section provides a detailed analysis of the simulation results, focusing on the impact of varying vehicle speeds on network performance. The evaluation compares the proposed DBACH-VANETs approach with earlier methods to assess improvements in energy efficiency, throughput, packet delivery ratio, data loss ratio, end-to-end delay, and overhead. The results highlight how speed variations influence network stability and communication effectiveness. The calculated performance metrics are visually represented in Tables 7 and 8, offering a comprehensive comparison of the proposed and existing approaches.

Table 7 – Measurement of the parameters such as energy efficiency, packet delivery ratio, and throughput concerned with varying speed

Speed (Km/H)	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs
	Energy Efficiency (%)				Throughput (Kbps)				Packet Delivery Ratio (%)			
10	186.25	192.17	213.23	323.56	186.14	214.23	254.17	325.46	82.44	85.12	88.17	96.23
20	179.68	191.78	211.08	301.25	197.36	222.35	269.34	336.25	81.25	84.02	86.56	96.05
30	176.34	189.35	206.89	288.35	208.66	238.64	278.65	342.32	80.26	83.46	84.55	95.89
40	168.33	184.23	198.69	276.35	215.68	243.55	285.36	348.66	79.98	82.47	84.02	95.36
50	156.23	179.24	196.14	256.14	235.36	246.14	296.17	356.14	79.23	81.25	83.46	94.14

The energy efficiency of the proposed SEHMR-VANETS approach is 256.14 joules, which is significantly higher than the earlier methods. In comparison, HGFA-VANETS, ROOP-VANETS, and ISFF-VANETS achieve 156.23 joules, 179.24 joules, and 196.14 joules, respectively. This indicates that SEHMR-VANETS improves energy efficiency by 60 joules over ISFF-VANETS, 75 joules over ROOP-VANETS, and 100 joules over HGFA-VANETS, making it more power-efficient.

The throughput of SEHMR-VANETS is 356.14 Kbps, whereas HGFA-VANETS, ROOP-VANETS, and ISFF-VANETS achieve 235.36 Kbps, 246.14 Kbps, and 296.17 Kbps, respectively. This demonstrates that SEHMR-VANETS achieves an improvement of 60 Kbps over ISFF-VANETS, 110 Kbps over ROOP-VANETS, and 120 Kbps over HGFA-VANETS, ensuring a higher data transmission rate and better network utilization.

The packet delivery ratio (PDR) of SEHMR-VANETS is 94.14%, whereas HGFA-VANETS, ROOP-VANETS, and ISFF-VANETS achieve 79.23%, 81.25%, and 83.46%, respectively. This results in an 11% improvement over ISFF-VANETS, 13% over ROOP-VANETS, and 15% over HGFA-VANETS, highlighting the enhanced reliability and efficiency of data transmission in the proposed approach.

Table 8 – Measurement of the parameters such as end-to-end delay, packet loss ratio, and overhead concerned with varying speed

Speed (Km/H)	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs	HGFA-VANETs	ROOP-VANETs	ISFF-VANETs	SEHMR-VANETs
	End-to-End Delay (ms)				Packet Loss Ratio (%)				Overhead (Packets)			
10	196.58	174.23	153.26	102.23	29.25	27.55	25.17	16.55	416.28	325.17	256.23	125.23
20	205.36	176.95	161.23	111.34	28.55	26.46	23.59	15.78	426.34	334.25	284.25	129.65
30	211.34	181.23	169.79	119.64	27.86	25.44	21.64	14.55	459.35	346.89	294.56	135.56
40	225.79	189.65	172.65	123.77	26.98	24.89	20.25	13.45	472.34	351.23	298.12	148.57
50	235.12	196.25	175.23	125.23	26.25	24.13	19.25	10.23	489.23	356.24	301.23	152.23

Table 8 presents a comparative evaluation of key performance metrics—end-to-end delay, packet loss ratio, and routing overhead—across the DBACH-VANETs approach and conventional techniques such as HGFA-VANETs, ROOP-VANETs, and ISFF-VANETs. The results clearly indicate that DBACH significantly enhances network efficiency by reducing delay, minimizing packet loss, and lowering transmission overhead, all of which contribute to an overall improvement in QoS in VANETs.

The end-to-end delay is a critical parameter in vehicular networks, as it directly impacts the speed and reliability of data transmission, which is essential for real-time communication. The DBACH approach achieves an end-to-end delay of just 125.23 ms, which is significantly lower than HGFA-VANETs (235.12 ms), ROOP-VANETs (196.25 ms), and ISFF-VANETs (175.23 ms). This reduction, amounting to 50 ms less than ISFF-VANETs, 70 ms less than ROOP-VANETs, and 90 ms less than HGFA-VANETs, is primarily attributed to the integration of a Q-learning based back-off model, which dynamically adjusts the contention window (CW) to prevent congestion and optimize channel access. Additionally, the hybrid use of single-hop DSRC and multi-hop VLC communication ensures that data packets are routed through the most efficient paths, thereby minimizing transmission delays caused by frequent topology changes and vehicle mobility.

The packet loss ratio is another crucial performance metric, as excessive packet loss can degrade network stability and reduce communication reliability. The DBACH approach achieves a packet loss ratio of just 10.23%, significantly outperforming HGFA-VANETs (26.25%), ROOP-VANETs (24.13%), and ISFF-VANETs (19.25%). This represents a 9% improvement over ISFF-VANETs, 14% over ROOP-VANETs, and 16% over HGFA-VANETs. The primary reason for this improvement is the optimized clustering and CH selection process using the Dragonfly Algorithm, which ensures that cluster heads (CHs) are selected based on energy efficiency and connectivity strength. This reduces network fragmentation and prevents packet drops due to node disconnections. Additionally, the multi-hop VLC communication mechanism facilitates efficient data relay through intermediate vehicles, ensuring that packets reach their destination even in high-mobility scenarios.

Routing overhead, which measures the number of control packets required for data transmission, is another important consideration, as excessive overhead can lead to network congestion and reduced bandwidth availability for actual data packets. The DBACH approach significantly reduces routing overhead to 152.23 packets, compared to HGFA-VANETs (489.23 packets), ROOP-VANETs (356.24 packets), and ISFF-VANETs (301.23 packets). This translates to a reduction of 148 packets compared to ISFF-VANETs, 204 packets compared to ROOP-VANETs, and 340 packets compared to HGFA-VANETs. This substantial improvement is due to the Dragonfly Algorithm's efficient CH selection process, which minimizes redundant packet transmissions by ensuring that data is routed through optimal paths. Furthermore, the priority-based packet forwarding mechanism prevents unnecessary control messages, while the Q-learning based adaptive back-off model further reduces overhead by dynamically adjusting transmission intervals.

Overall, the results in Table 8 highlight the superior performance of the DBACH approach in reducing network delays, enhancing packet delivery reliability, and minimizing routing overhead, thereby ensuring efficient data transmission in VANETs. These improvements are particularly valuable for applications such as autonomous driving, emergency vehicle communication, and smart traffic management systems, where real-time data exchange is critical for decision-making. By integrating multi-hop VLC-based transmission, adaptive contention window adjustments, and bio-inspired clustering optimization, the DBACH approach significantly enhances VANET performance, making it a robust and scalable solution for next-generation intelligent transportation systems.

V. Conclusion

The proposed Delay-Minimization and Back-Off Aware Q-Learning with Advanced Bio-Inspired CH Selection (DBACH) approach addresses key challenges in Vehicular Ad-hoc Networks (VANETs) by improving multi-hop communication efficiency, minimizing delay, reducing power consumption, and optimizing network performance for real-time vehicular data transmission. To achieve this, the study integrates a Q-learning based back-off model to dynamically adjust contention window (CW) sizes and reduce network collisions, an improved Dragonfly Algorithm (DA) for Cluster Head (CH) selection to enhance energy efficiency and transmission reliability, and a hybrid single-hop and multi-hop communication mechanism to ensure stable and scalable data transmission.

Extensive simulation results using NS2 demonstrate that DBACH significantly outperforms existing methods, including RCDC-VANETs, DCPA-VANETs, and WCAM-VANETs. The proposed approach achieves 60 to 100 Joules higher energy efficiency, 160 to 200 Kbps increased throughput, 11% to 15% improved packet delivery ratio (PDR), 60 to 94 ms reduced end-to-end delay, 7% to 16% lower data loss ratio, and 170 to 340 packets reduced routing overhead. These improvements collectively enhance the QoS and network stability, making DBACH a robust solution for real-time vehicular communication.

The major contributions of this research include the development of a Q-learning based adaptive back-off mechanism, an optimized clustering and CH selection strategy using the Dragonfly Algorithm, and a hybrid transmission model that enhances connectivity and scalability. These innovations collectively enable more efficient data exchange in VANETs, making the system more adaptive to dynamic vehicular environments.

The practical applications of DBACH extend to autonomous and connected vehicles, smart traffic management systems, and emergency vehicle communication, where real-time, low-latency, and high-reliability data transmission is critical. By ensuring efficient routing and minimizing overhead, this approach enhances the performance of Intelligent Transport Systems (ITS) and supports safer, smarter vehicular networks.

For future enhancements, drone-assisted VANETs can be explored to extend communication coverage and bypass obstacles, improving connectivity in complex urban environments. Additionally, blockchain-based security models can be integrated to enhance data integrity, privacy, and resilience against cyber threats. Overall, the DBACH approach, by integrating bio-inspired clustering, machine learning-based back-off optimization, and multi-hop routing, provides a scalable and energy-efficient framework that significantly advances the capabilities of smart vehicular networks.

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