Reliable Vehicular Ad Hoc Networks for Intelligent Transportation Systems based on the Snake Optimization Algorithm

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Received: 29 August 2024 | Revised: 19 September 2024 | Accepted: 27 September 2024

 DOI: https://doi.org/10.48084/etasr.8851

ABSTRACT

Vehicular Ad Hoc Networks (VANETs) represent an environment in which mobility exceeds the normal values, topology changes rapidly, and safety constraints are too high. The fundamental problem with VANETs is making transmission, acceptance, and sending out of messages between vehicles as timely, reliable, and secure as possible. The current study aims to address these challenges by applying the Snake Optimization Algorithm (SOA), enhancing network protocol efficiency, performance, and robustness. In this work, a comprehensive examination of the effects of optimal SOA on VANET protocols is provided over networks with different node sizes of 100, 250, and 500. End-to-end delay, path delivery overhead, and average number of hops improved after the utilization of SOA in all the considered networl configurations.

Keywords-VANETs; routing protocols; snake optimization algorithm; packet delivery ratio; end-to-end delay; scalability; adaptability

I. INTRODUCTION

VANETs are instrumental in unlocking a new dimension of our current transportation system, increasing its reliability, safety, and convenience [1]. Since people usually spend a lot of time driving, the introduction of smart vehicles equipped with VANET technology has a significant impact. These innovations must be viewed in such a way that they can increase safety, efficiency and satisfaction, while reducing pollution and costs. VANETs can play a vital role in reducing traffic congestion, lowering carbon emissions, and providing more accurate timetables, while enhancing the smart urban environment. In addition, VANETs are expected to be the backbone of smart cities in terms of advances in traffic management and environmental sustainability. VANETs are a critical component that supports the development of modern, responsive, safe, enjoyable, and environmentally friendly transportation networks. In modern, rapidly expanding urban environments, VANETs help solve traffic congestions, reduce greenhouse gas emissions, and ensure reliable traffic flow, so that cities can develop and present to the world their effectiveness in improving the quality of city life through modern transportation systems.

As an important part of Intelligent Transportation Systems (ITSs), VANETs are integrated with other ITS architectures such as Wide Area Networks (WANs) through Road Side Units (RSUs) to enhance security and download data from the Internet, including social media platforms [2, 3]. Initially, VANETs role was to improve and optimize traffic management and safety, while providing comfort and entertainment for drivers and passengers. Inter-vehicle communications, initially, involved vehicle-to-vehicle (V2V) communication [4], evolved to include Machine-to-Machine (M2M) communication, and eventually, Vehicle-to-Everything (V2X) communication [5]. In-vehicle units participating in VANETs facilitate distributed forms of wireless networking for data transfer among vehicles and allow cooperative communication within the boundaries of the RSUs. In VANETs, users are able to use, manipulate, rent, store, and share resources in a network software that executes critical applications over the network [6]. RSUs are supposed to play an important mediator role due to requests made by VANET users on the network. RSUs serve as the vehicle that connects users to travelers in cloud infrastructure technology.

Different types of cloud services are available (dynamic clouds, hybrid clouds, and micro-clouds) to receive incoming traffic and multimedia data through vehicular nodes. Cloud-based VANETs [7] ensure complete supervision of all vehicle locations which helps in collecting real-time traffic data and efficiently scheduling alerts targeting specific geographical locations and desired recipients. In the Internet of Vehicles (IoV) [2], ITCs face different types of Quality of Service (QoS) requirements, which creates a complex problem. Connected vehicles have played a real role in our daily lives and are poised to grow in their mobile data collection and data center processing capabilities. IoV will be able to solve many QoS requirements from a comprehensive perspective. The key contribution of this study is the development of an optimized VANET routing protocol. The basic VANET architecture can be seen in Figure 1 in [8].

SDN integration of software-based devices into VANETs [9] holds a leading position among current inventions and technologies of both industry and academia due to its great opportunities for the future. SDN is unique in that it separates the control plane and data plane of the router and allows them to be managed centrally. This separation results in a more dynamic network, as well as the ability to use network resources more rationally and efficiently in financing. Authors in [9] address the improvement of VANETs protocols through meta-heuristic algorithm optimization with special focus on Snake Optimization Algorithm (SOA). SOA is inspired by nature and is adaptable. As a result, it applies other principles to drive additional patterns to optimize network protocols.

The goal of the current research is to investigate the extent to which SOA can be used to improve and enhance the performance and effectiveness of VANET communication protocols. This investigation should ultimately lead to uncovering improvements to transportation systems, raising the quality of transportation as well as paying attention to the seamless flow of connected vehicles in today's smart city environment.

II. RELATED WORKS

The literature survey highlights recent VANET optimization advancements, including metaheuristic algorithms, QoS-driven protocols, and UAV-assisted communication for improved performance. Authors in [9] point out route protocols specifically designed for VANETs, citing Global Positioning System (GPS) positioning-based protocols as being as more suitable for highly mobile and dynamic vehicle encounters. A vehicular location-based routing protocol differs from typical Mobile Ad-hoc Network (MANET) protocols in that it exploits the geographical locations of vehicles to determine the optimal path for forwarding data. As a result, this type of routing protocol bypasses the need to exchange link state information and route maintenance. This paper aim to provide a broad and comprehensive overview of the benefits and drawbacks of such schemes which can help navigate future research. The issue is how to create a routing protocol which is a procedure targeting the special features of VANETs [10]. A VANET may be constantly changing, but the needs for a certain level of QoS are the same and this requires the development of optimization routing as well as scalable algorithms. The authors attempt to conduct a comprehensive survey of VANET protocols designed to work on QoS classification for different optimization methodologies as a basis for further research on QoS improvement in network routing in VANETs. Authors in [11] describe the main methods that serve routing protocols in establishing direct paths between sender and receiver devices. The Grasshopper Optimization Algorithm (GOA) for clustering nodes of VANETs, was discussed in [12]. Its goal was to optimize network throughput for uncertain node density scenarios where it outperformed many state-of-the-art algorithms. Exploiting the complexities and solutions of VANETs has been the central point of many studies. Studies have mainly sought to achieve this by optimizing routing protocols, QoS and network efficiency in reference to the dynamic topology of networks. Authors in [13] effectively addressed the cost model of the vehicle routing problem by considering network quality metrics and optimizing them when introducing the Jaya average computing algorithm to obtain the best paths and obtain better performance over the existing models in cost and convergence analysis. Authors in [14] primarily focus on solving the multi-constraint QoS optimal path problem using a feature of genetic algorithm as well as developing a specific cost function to control the optimization process of swarm-based algorithms, coupled with theoretical and experimental analysis. Authors in [15] emphasized the necessity of improving traffic efficiency as well as reducing congestion and enhancing communications reliability. When the installation of Unmanned Aerial Vehicles (UAVs) in VANETs is facilitated, intelligent routing algorithms can be designed to improve the data delivery efficiency and overall performance. Experimentation and result comparison between traditional routing techniques and UAV-assisted protocols show that in terms of throughput and packet delivery ratio, the latter reduces the MAC/physical layer protocol overhead.

Authors in [16] delved into the evolution of VANET routing technologies by incorporating bio-inspired methodologies. In addition, direct routing tasks for VANETs were discussed and routing-related techniques were reviewed. This paper presents a systematic classification that investigates different VANETs routing challenges using their characteristics, research methodology, and categories of metaheuristic strategies used in them. Furthermore, the authors depict more complex problems in VANET routes that can be favorably addressed by nature-inspired optimization algorithms. The study also details the performance of conventional and bio-inspired protocols in improving VANET routing.

Authors in [17] proposed a new approach that combines the establishment of a new route metric and a route optimization technique developed using improved genetic algorithm to meet the needs of VANET communication. Their proposed approach has higher routing efficiency than custom genetic algorithms do in conditions with uneven vehicle density. The proposed method contains the seeds that could enable secure communication between vehicles and improve road safety. Authors in [18] address VANETs and path selection laden with difficulties by proposing the Inherited Distance-Based Ant Colony Optimal Routing (IDBACOR). Contrasting comparisons with traditional routing protocols highlight that IDBACOR is structurally superior to traditional protocols in terms of throughput, communication cost, propagation delay, routing overhead, and packet delivery rate. This research adds significantly to the ongoing discussions on improving VANET routing efficiency and bringing ITSs to a higher level of safe and efficient transportation mode. Authors in [19] detail the practical performance evaluation of GSR (Geographic Source Routing) and RBVT-R (Road-Based using Vehicular Traffic-Reactive Routing) protocol in VANETs. To enhance the performance of RBVT-R, advanced optimization is applied by implementing Glowworm Swarm Optimization (GSO). The proposed routing selection algorithm captures the best feature path that includes average delay, packet delivery and hop count as QoS objectives. Comparative analysis between the GSO-RBVT-R and the GSR and RBVT-R- shows that the former has better accuracy in terms of several statistical measures.

In [20], a new type of routing protocol, RBVT, is presented that uses vehicular traffic as the main infrastructure. This scheme leverage short-term digital traffic information for each given vehicle to find the shortest route, including the maximum number of intersections. Implementing RBVT protocol on static traffic and providing an optimal forwarding mechanism improves protocol performance metrics such as delivery rate and delay compared to existing protocols in urban areas. Furthermore, the IMHA algorithm [21] was introduced to ensure that the QoS is improved by combining the function of d-PSO and ACO, which exposes a greater network throughput which in return results in less delay in data transmission.

An intelligent and innovative routing protocol clustering approach that leverages the ACO scheme, which ensures the stability and scalability of VANETs is described in [22]. The BHGWO (Bat Hybrid Gray Wolf Optimization) model has been proposed as an alternative for optimal path selection in VANETs in [23]. BHGWO model is an effective solution to obtain better performance metrics of congestion, delay, and energy. Another MANET protocol for IoT platforms which presents the optimized key management system and also highlights the performance of the proposed model in terms of statistical analysis, convergence analysis, and communication overhead is described in [24]. In [25], DyTE, an efficient routing protocol for VANETs in urban scenarios, exhibited significant improvements over traditional routing protocols. DyTE demonstrated a significant improvement in Packet Delivery Ratio (PDR) of approximately 23%, increased throughput of approximately 26%, and significantly reduced Network Routing Load (NRL).

Authors in [26] conducted research on the Seagull Optimization Algorithm with Share Creation for VANETs and demonstrated significant advancements in security measures for smart vehicles in 5G networks. By integrating this innovative algorithm, they achieved enhanced data confidentiality, access control, and data privacy within VANETs. The results showed improved encryption strength and authentication accuracy, leading to a more secure communication framework.

III. ROAD-BASED USING VEHICULAR TRAFFIC ROUTING PROTOCOL (RBVT-P AND RBVT-R)

This section introduces the RBVT class for city-based VANET routing protocols. These protocols utilize real-time vehicular traffic data to establish road-based routes, which consist of a series of road intersections with a high likelihood of network connectivity. By leveraging any node on a road segment to forward packets between successive intersections on the route from source to destination, geo-forwarding reduces the path's dependency on the movements of individual nodes. Road-based routes are generated by the RBVT class of routing protocols using real-time vehicle traffic information. RBVT technology has two primary benefits: (1) route stability via geo- forwarding and road-based routing and (2) adaptation to network conditions by adding real-time vehicle traffic information.

RBVT pathways can be proactively or reactively generated. Two RBVT protocols—the proactive protocol, RBVT-P, and the reactive protocol, RBVT-R—were created and put into practice, each of which demonstrated a different path building technique. Routes are found by RBVT-R on-demand and are included in the packet headers (source routing). On the other hand, RBVT-P records the graph of the vehicle traffic in real time and creates connection packets on a regular basis that visit all of the connected road segments.

A. RBVT-R: Reactive Routing Protocol

RBVT-R is a reactive source routing system designed for VANETs that use "connected" road segments to create road-based routes or paths on demand. A connected road segment runs between two nearby intersections and has sufficient traffic to provide connectivity to the network. The data packet headers contain these routes, which are sequences of intersections that intermediate nodes use to geographically forward packets between junctions.

B. RBVT-P: Proactive Road-Based Routing

To maintain a fairly constant image of the network topology at each node, RBVT-P periodically finds and distributes the route-based network topology. Context: Road-based networks are built using Connectivity Packets (CPs). CPs in the network are unicast broadcasted. CPs save their endpoints or intersections in the packet as they move across road segments. Using this traversal technique, CPs can throttle the majority of the load associated with common proactive MANET protocols. After completing the network traversal, the topology data in the CP is output and saved in a route update (RU) packet, which is then distributed to every node in the network (i.e. the area covered by the CP). Simulation of the proposed systems were run in OMnet++ utilizing the vehicle mobility created by the simulation of urban mobility (SUMO). Figure 1 shows the flow chart of the proposed system.

IV. DESIGN OF SNAKE OPTIMIZATION ALGORITHM FOR RBVT

In this work, SOA [27] is proposed to optimize the sound of VANET protocols in routing performance. A snake chooses its future travel path based on the distance and direction between its current position and the food's location [28]. SOA is based on the foraging behavior of snakes, and is grouped into a etachronistic approach. This sense of adaptability and flexibility makes it a most suitable candidate for optimizing VANET protocols with respect to routing performance in particular. The optimization effects are evident as one can see noticeable improvements in various performance metrics within the network, which are observed after implementation. Exploration and exploitation are the two phases of feeding. In SOA, the population is separated into males and females which does not happen in other optimization algorithms. In this algorithm, optimization starts with support from randomly generated populations. Temperature T plays a major role in this algorithm. Mathematically T is written as follows [29]:

$$T = e^{(-t/T)} \quad (1)$$

Where the current iteration number is mentioned by t and the maximum number of iterations is represented by T. The quantity of the food (Q) taken by a snake is:

$$Q = 0.5 * e^{\frac{t-T}{T}} \quad (2)$$

If the value of Q is less than 0.25, the snake is in an inadequate food and exploration phase. In this phase, snakes are searching their foods randomly. Figure 2 shows the flowchart for the SOA. Food quantity plays a major role in differentiating the exploaration and exploitation performance states.

A. Snake Movement Calculation

Assume that at the i^{th} stage of the optimisation process, the snake's current position is x_i and the target position (food location) is x_{target}. The snake determines the unit vector for movement direction (D) based on the distance between its current and goal positions:

$$D = \frac{x_{target} - x_i}{|x_{target} - x_i|} \quad (3)$$

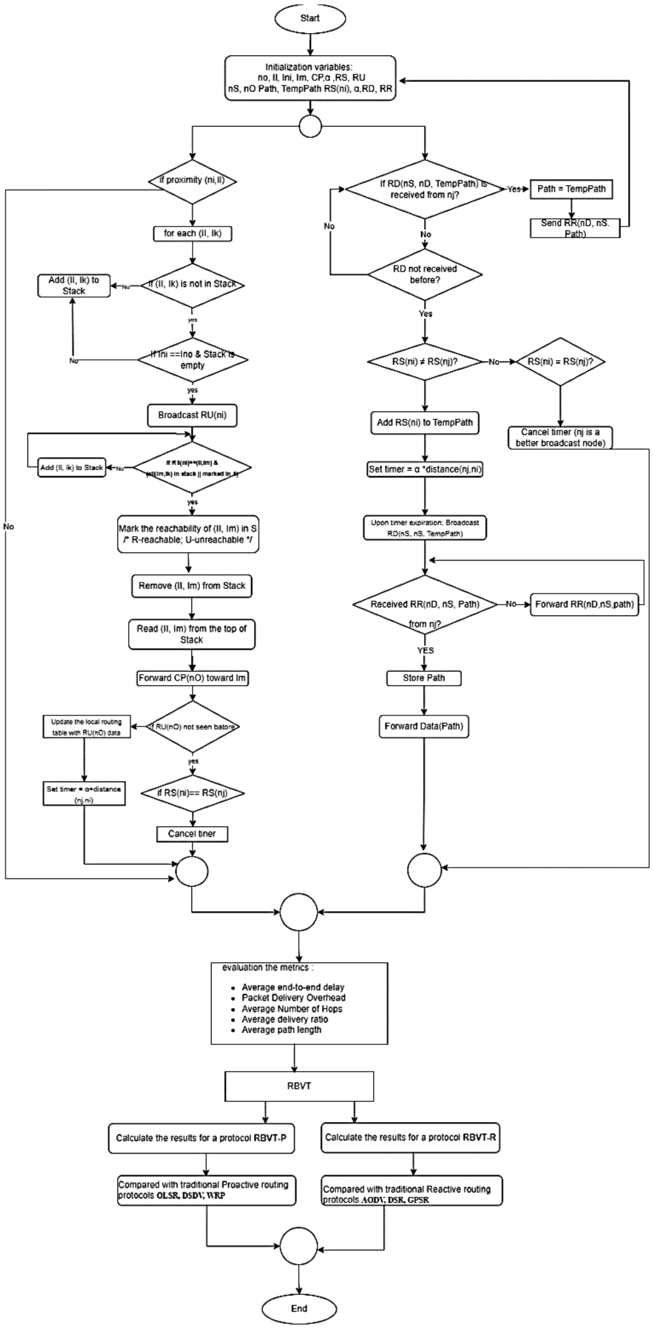


Fig. 1. Detailed flowchart illustrating the operational process of the proposed system.

B. Snake Position Updating

The snake adjusts its position depending on the size of the step and the direction of movement:

$$x_{i+1} = x_i + \text{step size} * \text{direction of movement} \quad (4)$$

where i represents the up-to-date optimization step.

C. Food Attraction

To mimic a snake's interest in food, a directional motion attractant factor can be added to push it toward the target:

$$D = \frac{x_{target} - x_i}{|x_{target} - x_i|} + \text{Attract} * (x_{target} - x_i) \quad (5)$$

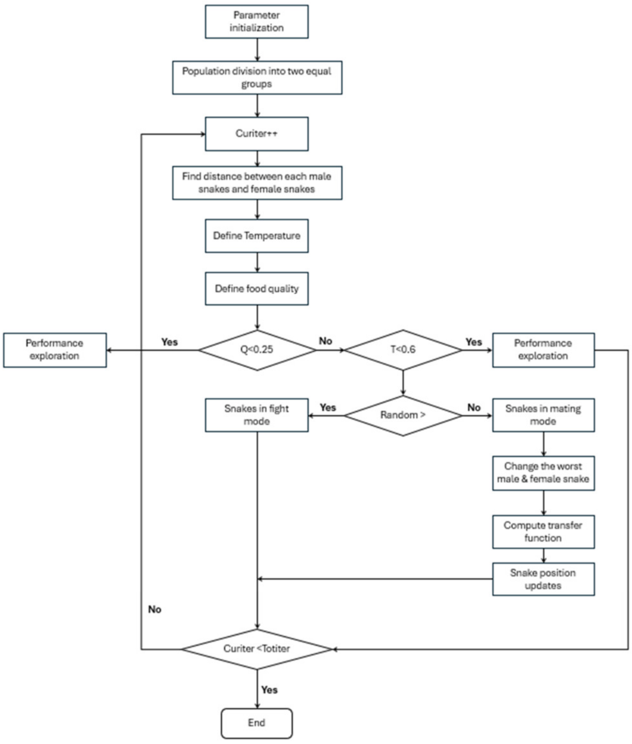


Fig. 2. SOA flowchart.

D. Dynamic Step Size

Dynamic step sizing can help avoid stopping the optimization process in local optima. This approach gradually reduces the step size during optimization:

$$\text{Step} = \frac{\text{Initial step}}{1 + i * \text{step decay}} \quad (6)$$

Because of its adaptability and flexibility, this algorithm is the ideal choice for optimizing VANET protocols, particularly in terms of routing performance. The routing protocol parameters can be adjusted in accordance with the network characteristics and thus improve the protocol performance while reducing packet and listening delays and system overhead.

SOA may face challenges in high-density networks, dynamic topologies, and environments with unpredictable mobility, leading to increased computational overhead and slower convergence in complex scenarios.

V. EXPERIMENTAL RESULTS

In the simulations, a 400×400 m² area was used, with a total simulation time of 100 s. The number of nodes varied between 100, 250, and 500, and each node was moving at a speed of 25 m/s. The transmission range was set to 250 m, and the physical layer protocol used was 802.11b with a transmission power of 1 mW. The routing protocol implemented was RBVT, with a Hello interval of 1 s, and a total of 5 Hello messages were transmitted during the simulation.

A. Average End-to-End Delay

Table I provides a comprehensive comparison of the average end-to-end delay values for the RBVT-R and SOA-RBVT-R protocols across different node configurations. For the RBVT-R protocol, the delays for 100 nodes are 0.981 ms, 1.954 ms, and 2.698 ms, while the SOA-RBVT-R protocol shows delays of 0.897 ms, 0.31 ms, and 0.764 ms. This trend continues at 250 nodes, where RBVT-R records delays of 0.93 ms, 1.76 ms, and 2.56 ms, compared to SOA-RBVT-R delays of 0.785 ms, 0.945 ms, and 0. 295 ms. For 500 nodes, the RBVT-R delays are 2.65, 4.58, and 2.89 ms, while the SOA-RBVT-R delays are 0.919, 0.853, and 0.782. It can be concluded that SOA-RBVT-R protocol reduces end-to-end delays, especially as the network size increases. The SOA reliably reduces latency, improving data transfer across node densities, especially as network size grows. Across node densities, the SOA variant always has a shorter latency, indicating better performance and efficiency in data transfer. The SOA-RBVT-R protocol is more reliable for different network setups because it reduces latency, thus improving network communication.

TABLE I. AVG END-TO-END DELAY COMPARISON BETWEEN RBVT-R AND SOA-RBVT-R PROTOCOLS ACROSS DIFFERENT NODE CONFIGURATIONS

Packet Rate (packets/s)	Average end-to-end delay(ms)					
	Nodes=100		Nodes=250		Nodes=500	
	RBVT-R	SOA-RBVT-R	RBVT-R	SOA-RBVT-R	RBVT-R	SOA-RBVT-R
2	0.981	0.897	0.93	0.785	2.65	0.919
4	1.954	0.31	1.76	0.945	4.58	0.853
6	2.698	0.764	2.56	0.295	2.89	0.782
8	3.445	0.576	3.33	0.682	1.18	0.844
10	3.85	0.569	1.92	0.792	2.35	0.945

TABLE II. AVG END-TO-END DELAY COMPARISON OF RBVT-R AND SOA-RBVT-P PROTOCOLS

Packet Rate (packets/s)	Average end-to-end delay(ms)					
	Nodes=100		Nodes=250		Nodes=500	
	RBVT-P	SOA-RBVT-P	RBVT-P	SOA-RBVT-P	RBVT-P	SOA-RBVT-P
2	1.2	0.223	2.11	0.453	1.34	0.91
4	3.2	0.903	4.53	0.852	2.68	0.88
6	2.5	0.987	2.51	0.22	4.11	0.37
8	1.1	0.193	3.89	0.786	5.61	0.47
10	5.2	0.874	2.59	0.386	3.67	0.69

In Table II, the average end-to-end delay values of RBVT-P and SOA-RBVT-P protocols are compared. It can be seen that the response time (latency) of SOA-RBVT-P decreases as the network grows to 250 nodes. However, the SOA-RBVT-P protocol maintains improved performance. In all node configurations, the SOA-RBVT-P protocol consistently shows lower end-to-end delays compared to the RBVT-P protocol. ms. This comparison confirms the effectiveness of the SOA-RBVT-P protocol in reducing end-to-end delay, especially as the network size increases. The SOA variant reliably achieves lower delays, indicating improved performance and efficiency in data transfer across different node densities.

(a)

(b)

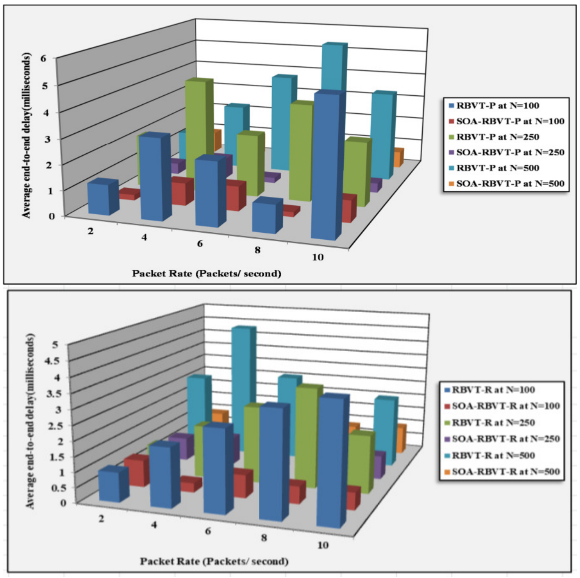


Fig. 3. Experimental results for average end-to-end delay: A comparative analysis of 100, 250, and 500 node networks before and after applying the SOA. (a) Proactive, (b) reactive protocols.

Figures 3 provides a detailed comparative analysis of the average end-to-end delay for different packet rates across different node configurations. The superior performance of the proposed protocols can be clearly seen.

B. Packet Delivery Overhead

Tables III and IV compare the packet delivery overhead of RBVT and SOA-RBVT the reactive and proactive versions, respectively. It can be seen that SOA-RBVT has much lower packet delivery overhead than RBVT. The comparisons show that the SOA modifications of the RBVT-R and RBVT-P protocols significantly reduce packet delivery overhead. Reducing overhead increases network efficiency and scalability at different node densities and packet rates.

TABLE III. COMPARISON OF PACKET DELIVERY OVERHEAD BETWEEN RBVT-R AND SOA-RBVT-R

Packet Rate (packets/s)	Packet delivery overhead (packets/s)					
	Nodes=100		Nodes=250		Nodes=500	
	RBVT-R	SOA-RBVT-R	RBVT-R	SOA-RBVT-R	RBVT-R	SOA-RBVT-R
2	1.228	0.193	1.42	0.199	0.98	0.78
4	2.31	0.782	1.93	0.293	1.47	0.56
6	1.51	0.853	2.41	0.573	1.52	0.74
8	1.42	0.989	3.51	0.675	2.1	0.87
10	1.73	0.773	1.94	0.381	1.25	0.71

TABLE IV. COMPARISON OF PACKET DELIVERY OVERHEADS BETWEEN RBVT-P AND SOA-RBVT-P

Packet Rate (Packets/s)	Packet delivery overhead (packets/s)					
	Nodes=100		Nodes=250		Nodes=500	
	RBVT-P	SOA-RBVT-P	RBVT-P	SOA-RBVT-P	RBVT-P	SOA-RBVT-P
2	1.18	0.536	1.79	0.819	0.65	0.46
4	1.54	0.679	2.65	0.791	0.97	0.79
6	4.5	0.199	5.18	0.582	1.96	0.94
8	3.21	0.103	4.53	0.931	1.97	0.38
10	4.21	0.21	3.41	0.825	1.36	0.68

(a)

(b)

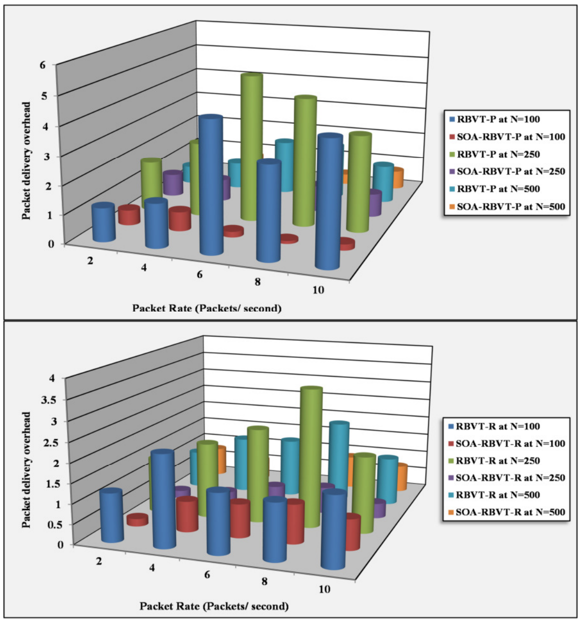


Fig. 4. Experimental results for packet delivery overhead: A comparative analysis of 100, 250, and 500 node networks before and after applying the SOA. (a) Proactive, (b) reactive protocols.

Figure 4 shows a detailed comparative analysis of packet delivery overhead for different packet rates (packets/s) across the considered node configurations, for both reactive and proactive protocol versions. This figure clearly shows how SOA optimizations reduce packet delivery overhead across different network sizes and packet rates. This consistent reduction in packet delivery overheads for SOA-RBVT highlights its enhanced efficiency and performance, especially in larger networks.

C. Average Path Length

The average path length of RBVT-P and SOA-RBVT-P at the 100, 250, and 500 node settings is shown in Table V. The hops per packet determine the average trip length. At 2 packets per second, the RBVT-P protocol has an average path length of 1.3 hops for a 100-node arrangement, while the SOA-RBVT-P protocol reduces this to 0.734 hops. When the packet rate increases to 10 packets per second, the path length of RBVT-P is 5.3 hops, but the path length of SOA-RBVT-P is 0.986 hops, indicating its efficiency in reducing path lengths. At 2 packets per second in a 250-node system, the average path length for RBVT-P is 1.33 hops, while SOA-RBVT-P has 0.786 hops. With 10 packets per second, the path length of RBVT-P is 3.76 hops compared to SOA-RBVT-P's 0.831. SOA-RBVT-P consistently has shorter paths across packet rates. At 2 packets per second, RBVT-P has an average path length of 1.99 hops for a 500-node configuration, while SOA-RBVT-P has 0.795 hops. RBVT-P has a path length of 4.36 hops at 10 packets per second, while SOA-RBVT-P has 0.223 hops. These results show that SOA-RBVT-P significantly reduces average path lengths, which improves routing efficiency.

The average path lengths for the RBVT-R and SOA-RBVT-R protocols across 100, 250, and 500 nodes are shown in Table VI. In a 100-node system with 2 packets per second, the average path length of RBVT-R is 1.25 hops, while SOA-RBVT-R has 0.897 hops. When the packet rate is 10 packets per second, RBVT-R reports a path length of 1.93 hops, but SOA-RBVT-R shows 0.786 hops. This reduction in path length shows the efficiency advantages of SOA-RBVT-R. RBVT-R averages 2.78 hops per packet at 2 packets per second for a 250-node configuration, while SOA-RBVT-R reduces this to 0.691 hops. The RBVT-R has 1.94 hops and the SOA-RBVT-R has 0.931 hops at a rate of 10 packets per second. These results demonstrate that SOA-RBVT-R reduces route durations at different packet speeds. At 2 packets per second in a 500-node system, RBVT-R has an average path length of 1.64 hops, while SOA-RBVT-R has 0.97 hops. RBVT-R has a path length of 4.21 hops at 10 packets per second, but SOA-RBVT-R reduces it to 0.57. These results demonstrate the ability of SOA-RBVT-R to shorten paths, enhancing routing efficiency.

TABLE V. COMPARISON OF AVERAGE PATH LENGTHS BETWEEN RBVT-R AND SOA RBVT-R

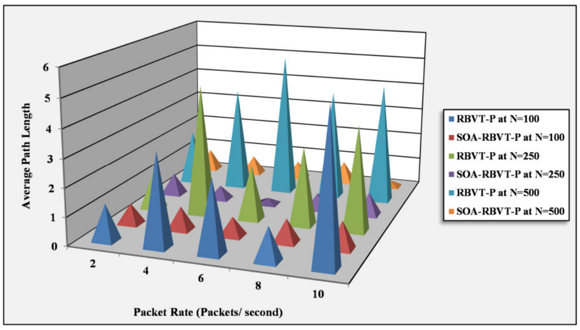
Packet Rate (packets/s)	Average Path Lengths (hops)					
	Nodes=100		Nodes=250		Nodes=500	
	RBVT-P	SOA-RBVT-P	RBVT-P	SOA-RBVT-P	RBVT-P	SOA-RBVT-P
2	1.3	0.734	1.33	0.786	1.99	0.795
4	3.3	0.827	4.72	0.497	3.79	0.698
6	2.6	0.678	1.98	0.218	5.21	0.644
8	1.2	0.834	2.82	0.612	3.98	0.821
10	5.3	0.986	3.76	0.831	4.36	0.223

TABLE VI. COMPARISON OF AVERAGE PATH LENGTHS BETWEEN RBVT-P AND SOA RBVT-P

Packet Rate (packets/s)	Average Path Lengths (hops)					
	Nodes=100		Nodes=250		Nodes=500	
	RBVT-R	SOA-RBVT-R	RBVT-R	SOA-RBVT-R	RBVT-R	SOA-RBVT-R
2	1.25	0.897	2.78	0.691	1.64	0.97
4	2.53	0.645	2.91	0.987	2.76	0.73
6	3.11	0.345	4.64	0.895	3.75	0.81
8	3.45	0.289	2.76	0.11	2.94	0.72
10	1.93	0.786	1.94	0.931	4.21	0.57

Figure 5 compares the average path lengths for different packet rates across the considered node configurations. The figures highlight the performance differences between the RBVT and SOA-RBVT protocols, either reactive (Figure 5(a)) or proactive (Figure 5(b)). This figure shows how well the SOA-RBVT protocol reduces path lengths across network sizes and packet speeds, in both considered versions.

(a)



(b)

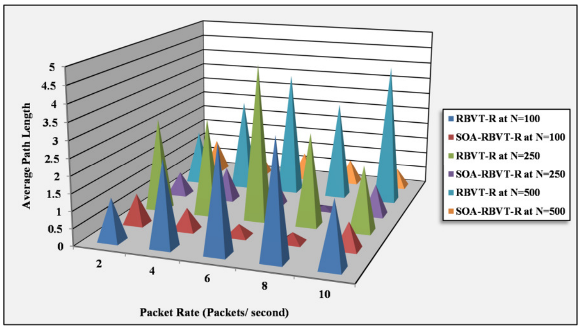


Fig. 5. Average path length: Comparison across 100, 250, and 500 node networks. (a) Proactive, (b) reactive protocols.

D. Average Delivery Ratios

The average delivery ratios for the RBVT-P and SOA-RBVT-P protocols in the 100, 250, and 500 node topologies are shown in Table VII. The average delivery ratio, a unitless metric, compares the successfully delivered packets to the sent packets to determine the efficiency of packet delivery.

At 2 packets per second in a 100-node arrangement, the RBVT-P protocol has an average delivery ratio of 1.3, whereas the SOA-RBVT-P protocol has 0.912. When the packets per second reach 10, RBVT-P has a delivery ratio of 5.3, whereas SOA-RBVT-P decreases to 0.236. As packet rates grow, RBVT-P exceeds SOA-RBVT-P in delivery efficiency. RBVT-P has an average delivery ratio of 0.99 at 2 packets per second for 250 nodes, while SOA-RBVT-P has 0.647. The delivery ratio of RBVT-P is 2.67 at 10 packets per second, compared to 0.289 for SOA-RBVT-P. These data indicate that RBVT-P outperforms SOA-RBVT-P in delivery ratio for this node size. RBVT-P has an average delivery ratio of 2.98 at 2 packets per second in a 500-node configuration, while SOA-RBVT-P has 0.96. At 10 packets per second, the RBVT-P delivery ratio is 1.78, while the SOA-RBVT-P delivery ratio is 0.72. These results show that RBVT-P consistently delivers more packets at varying packet speeds and network sizes.

The average delivery ratios of RBVT-R and SOA-RBVT-R across 100, 250, and 500 nodes are shown in Table VIII. RBVT-R has an average delivery ratio of 1.6 at 2 packets per second per 100 nodes, while SOA-RBVT-R has 0.643. The delivery rates of RBVT-R are 4.10 and SOA-RBVT-R 0.812 at 10 packets per second. As the packet rate increases, RBVT-R exceeds SOA-RBVT-R in delivery efficiency. At 2 packets per second, RBVT-R has a delivery ratio of 1.11 in a 250-node configuration, compared to 0.643 for SOA-RBVT-R. At 10 packets per second, the RBVT-R is 3.97 and the SOA-RBVT-R is 0.691. This shows that RBVT-R outperforms SOA-RBVT-R in delivery ratio for this node size. RBVT-R has an average delivery ratio of 1.85 in a 500-node network at 2 packets per second, while SOA-RBVT-R has 0.876. The delivery ratio of RBVT-R is 1.1 at 10 packets per second, while the delivery ratio of SOA-RBVT-R is 0.897. RBVT-R outperforms SOA-RBVT-R in delivery ratios across packet rates and network sizes.

Figure 6 shows the average delivery ratios of all the considered protocols and different packet rates across different node configurations.

TABLE VII. COMPARISON OF AVERAGE DELIVERY RATIOS BETWEEN RBVT-P AND SOA RBVT-P

Packet Rate (packets/s)	**Average Delivery Ratio**					
	Nodes=100		**Nodes=250**		**Nodes=500**	
	RBVT-P	SOA-RBVT-P	RBVT-P	SOA-RBVT-P	RBVT-P	SOA-RBVT-P
2	1.3	0.912	0.99	0.647	2.98	0.96
4	3.3	0.829	1.39	0.987	2.56	0.86
6	2.6	0.78	1.95	0.645	2.5	0.95
8	1.2	0.647	2.55	0.345	1.69	0.61
10	5.3	0.236	2.67	0.289	1.78	0.72

TABLE VIII. COMPARISON OF AVERAGE DELIVERY RATIOS BETWEEN RBVT-R AND SOA RBVT-R

Packet Rate (packets/s)	**Average Delivery Ratio**					
	Nodes=100		**Nodes=250**		**Nodes=500**	
	RBVT-R	SOA-RBVT-R	RBVT-R	SOA-RBVT-R	RBVT-R	SOA-RBVT-R
2	1.6	0.643	1.11	0.643	1.85	0.876
4	2.2	0.723	1.48	0.761	2.5	0.988
6	2.9	0.837	2.66	0.583	1.69	0.596
8	1.4	0.939	2.39	0.185	1.18	0.287
10	4.6	0.812	3.97	0.691	1.1	0.897

(a)

(b)

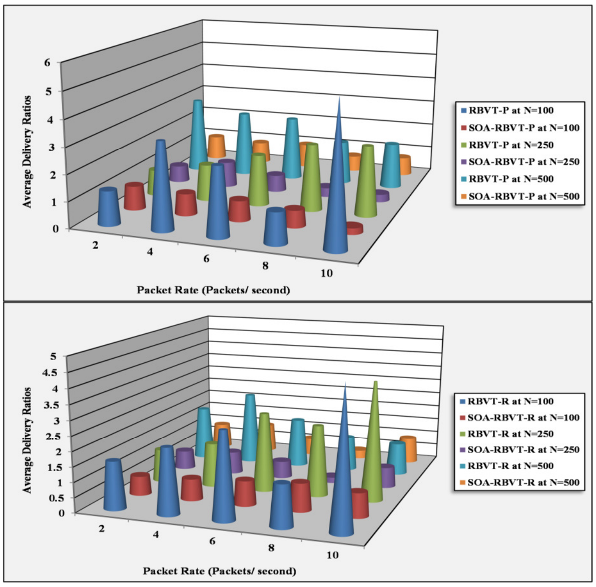


Fig. 6. Average delivery ratio: Comparison across 100, 250, and 500 node networks. (a) Proactive, (b) reactive protocols.

E. Comparative Analysis

1) Average End-to-End Delay

End-to-end delay is a key indicator of real-time performance in communications. The comparison of post-optimization and pre-optimization results indicates reduced delay across all network sizes although the 500-node network shows the most notable delay reduction as a result which can be evaluated in different real-time communication scenarios after optimization. The comparative analysis clearly shows the efficiency of SOA in enhancing different network performance metrics within networks regardless of their size. Besides the overall progress of all networks, the improvement levels were different for each due to the size of the networks and metrics.

2) Packet Delivery Overhead

Packet delivery overhead is a strong manifestation of the need for additional resources required in the network environment to successfully transmit the required data. Headcount reduction constitutes a significant portion of post-optimization overhead. In the 100-node network, using the optimization algorithm resulted in the largest overhead reduction because smaller networks seem to benefit more by the algorithm than larger networks.

3) Average Path Length

Average path length (average number of hops) shows the distance between nodes that a packet travels through the network. The proposed optimization algorithm showed a reduction in the average hop count across all network sizes with maximum performance on the network of 250 nodes.

4) Average Delivery Ratio

Average Delivery Ratio helps evaluate the packet delivery process in networks and even determine its efficiency. Moreover, an analysis of this metric comparing the optimization algorithms used for different network sizes should reveal their impact on the convergence process. Interestingly, growth in delivery ratio was notices when the size of the network grew bigger. The proposed SOA-protocols did not surpass their counterparts across all sizes and topologies.

VI. CONCLUSION

This study provided a comprehensive examination of the effects of optimal SOA on VANETs across networks with different node sizes of 100, 250, and 500. The effectiveness of the proposed algorithm was evaluated thoroughly.

End-to-end delay, packet delivery overhead, and average path length exhibited improved values when the SOA algorithm was implemented in the RBVT protocol, in both, reactive and proactive, configurations and all considered network sizes.

In this study, the proposed work was implemented in simulation only. In the future, this same protocol will be performed in hardware setup. In the future, some other optimization algorithms for VANETs can be used in intelligent transportation systems. For future work, testing SOA in real-world environments and exploring hybrid optimization techniques is recommended.

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