Optimization of AODV Routing in VANETs Using Grasshopper, PSO, and Genetic Algorithms

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Inter-vehicular networks (VANETs), a subset of mobile ad hoc networks, face significant routing challenges due to rapid topology changes caused by fast-moving nodes. This study proposes a method to enhance the Ad Hoc On-Demand Distance Vector (AODV) routing protocol in VANETs using nature-inspired optimization algorithms, namely Grasshopper Optimization Algorithm (GOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). The optimization problem is defined as finding optimal values for 11 AODV control parameters to maximize packet delivery ratio (PDR), minimize average end-to-end delay (E2ED), and reduce normalized routing load (NRL). The methodology involves integrating these algorithms with NS-2 simulations, where a VANET scenario with 50 vehicles in a 670×670 m² urban area is modeled. The fitness function, combining PDR, E2ED, and NRL with weights of 0.2, 0.5, and 0.3, respectively, guides the optimization process. Experimental results show that GOA and PSO achieved a PDR of 100% (compared to 97.46% for GA), reduced NRL to 0.34% (from 0.62% for GA), and maintained E2ED at 12.32 ms (compared to 11.05 ms for GA). The fitness function value improved to -0.508 for GOA and PSO, outperforming GA's -0.514. These findings demonstrate the effectiveness of nature-inspired algorithms in enhancing AODV routing performance in VANETs.

Povzetek: Članek raziskuje optimizacijo AODV usmerjevalnega protokola v omrežjih VANET z uporabo treh algoritmov po vzoru narave: Grasshopper Optimization (GOA), Particle Swarm Optimization (PSO) in genetski algoritem (GA). Avtorja definirata večciljno funkcijo za izboljšanje treh ključnih metrik kakovosti storitev (PDR, E2ED, NRL) in pokažeta, da GOA in PSO omogočata hitrejšo konvergenco in boljšo robustnost v dinamičnih prometnih scenarijih.

1 Introduction

In today's advanced societies, with the ever-increasing population growth and the rise in the count of cars, the issue of traffic has become one of the biggest challenges in transportation. Boosting routing in inter-vehicle networks is very important because it can help reduce traffic, optimize travel time, and save fuel consumption [1]. Factors such as changes in traffic, multiple and complex routes, and coordination between vehicles further complicate this issue. For this reason, much research has been done to boost routing in inter-vehicle networks [2]. One of the effective approaches to improving routing is the use of nature-inspired algorithms, such as GOA, PSO, and GA, which are well-suited for VANETs due to their ability to efficiently explore complex, high-dimensional parameter spaces and adapt to dynamic topology changes caused by vehicle mobility. Unlike traditional optimization methods, which struggle with the computational complexity of tuning multiple AODV parameters, these metaheuristic algorithms mimic natural processes (e.g., swarm behavior, evolution) to find near-optimal solutions quickly [3]. By connecting cars to the network and sharing information, it is possible to boost routing in inter-vehicle networks [4]. Internet of Things technology, with the possibility of interaction between cars, sensors, and traffic management systems, can significantly improve the routing of cars in inter-vehicle networks. This technology makes it feasible to collect and review data on the whereabouts, speeds, and traffic situations of vehicles and provide drivers with the best routes [5]. Inter-vehicle networks allow moving vehicles in cities and on suburban roads to possibly share information and data with other vehicles and make use of information gathered by roadside equipment [6]. The high accident rate often results from drivers' lack of real-time information about obstacles or traffic conditions. ITS systems address this by enabling vehicles to share Cooperative Awareness Messages (CAMs) and Decentralized Environmental Notification Messages (DENMs), which provide warnings about hazards (e.g., collisions, roadworks, sudden braking), traffic jams, or vehicle states (e.g., location, speed, direction), thereby enhancing driver awareness and reducing accident risks [7]. Any safety-related information, such as warnings to prevent collisions, traffic jam conditions, or non-safety information like weather and travel advice, can be received by every automobile. It can also learn details about other cars' current conditions, like their location, speed, and direction of travel. For the driver's next move, such as altering the car's speed or direction, this information can be very helpful [8]. Like other emerging technologies like nanoelectronics and nanorobotics [9], [10], one of the key characteristics of inter-vehicle networks is their high speed and rapid topology change, which forces nodes to continually update their routing information. This network's frequent topology changes are thought to present significant routing challenges. Therefore, routing for data transmission in these networks is a very important and necessary issue. In general, there are two tactics for routing in inter-vehicle networks, which are separated into two groups: routing drawing on topology and routing drawing on geographic location [11]. The information in the network is used to send packets via routing protocols drawing on topology, whereas routing tactics drawing on geographic location employ node location information for routing [12]. VANETs are known as networks whose topology changes rapidly, and the wireless coverage of these networks depends on the surrounding conditions, including the presence of nearby buildings and cars [13]. In addition, the lack of a central control unit in VANET networks has made routing in these networks a critical and difficult task. For this reason, researchers have presented many articles in which a new protocol has been presented or the existing protocols have been improved [14]. One of the techniques for improving routing protocols is to discover the ideal value for the parameters that control the productivity of that protocol. However, due to the large number of possible answers, finding the optimal value in most protocols is not a simple task. As a result, because they take a very long time to execute, the current approaches cannot be used to address optimization problems [15]. In the computer field, meta-heuristic schemes have arisen as powerful and adaptable tactics for optimization and search issues, which have been used in several problems and have achieved a high level of solution [16]. For this reason, meta-heuristic schemes have been used in this research to boost the AODV routing protocol in VANET's network. Utilizing locust schemes, particle swarms, and genetics, the ideal value for the control parameters of the AODV protocol has been calculated. Quality of service (QoS) metrics are used to evaluate the outcomes, and each of the three schemes' effects on routing performance and the development of the AODV protocol are contrasted. A summary of the authors' contributions to this investigation is given below:

Providing a method for improving routing in inter-vehicle networks using schemes inspired by nature (such as the grasshopper algorithm, particle swarm algorithm, and genetic algorithm), applying these schemes to the parameters of the AODV routing protocol, and evaluating the paper's performance using packet delivery rate criteria, average end-to-end delay, and normalized routing load.

The primary research objective is to enhance the performance of the AODV routing protocol in VANETs by optimizing its control parameters using nature-inspired algorithms (GOA, PSO, GA). The research question is: How effectively can nature-inspired algorithms optimize AODV parameters to improve Quality of Service (QoS) metrics, such as packet delivery ratio (PDR), end-to-end delay (E2ED), and normalized routing load (NRL), in dynamic VANET environments? We hypothesize that these algorithms, particularly GOA, will outperform traditional parameter settings by achieving higher PDR, lower E2ED, and reduced NRL due to their ability to efficiently explore the parameter search space. Expected outcomes include a PDR above 95%, E2ED below 20 ms, and NRL below 0.5%, aligning with VANET requirements for real-time applications.

This study contributes to: (a) proposing a method to improve VANET routing using nature-inspired algorithms, (b) applying these algorithms to optimize 11 AODV control parameters within predefined ranges through NS-2 simulations, and (c) evaluating the performance using PDR, E2ED, and NRL to ensure reliable, low-latency, and low-overhead routing.

The remainder of the exploration is outlined below:

In the second part, previous studies and their challenges are discussed, and in the third part, brief explanations of the schemes used in this research are given. In the fourth section, the AODV routing protocol and its control parameters are introduced, and in the fifth section, network evaluation parameters and the cost function are defined to check the optimization process. The recommended work tactic is explained in the sixth part, and in the seventh part, the simulation scenario and parameters are explained. The evaluation of the network is presented, and finally, the outcomes of this investigation are analyzed in the eighth part.

2 Related works

The tactics described here are derived from real-world instances in biology, nature, and technology. These tactics don't require prior knowledge of the issue area and can be applied to diverse NP-hard optimization issues [17]. Metaheuristics provide speedy identification of the best solution when used in conjunction with effective search techniques. Routing in VANET was discovered to be an NP-hard problem. Several CBR approaches include clustering schemes as an essential component [18]. Clustering makes use of multi-objective problems [19]. Ad hoc network routing is especially affected by these MOPs. Several variables affect how well conventional QoS works. Bandwidth employment, average end-to-end delay, and packet delivery proportion are all examples of such metrics. Some of the benefits of clustering optimization include topology stability, data aggregation, cluster reduction, bandwidth optimization, and efficient transmission management [20]. VANETs are essential in several Intelligent Transportation System (ITS) technologies, encompassing effective traffic management, media applications, and secure financial transactions. The adaptive nature of the vehicle network's topology is influenced by the growing traffic volume, which poses challenges to the network's scalability due to the scattered distribution of automobiles on roadways. Therefore, there is a challenge for all vehicles (in the network) to keep a steady path, which increases the fluctuation of the network. This paper [21] presents a recommended algorithm, known as the probabilistic nature-based intelligent whale optimization algorithm (p-WOA), for routing in IoT-based network transport. The approach is bio-inspired and cluster-based, with a focus on creating clusters in vehicles. The study incorporated the examination of other variables, including communication range, count of nodes, speed, and route along the highway. The probabilities associated with these characteristics were integrated into the fitness function, leading to a reduction in randomness. The findings were compared to established methodologies, including ant milk optimizer (ALO) and gray wolf optimization (GWO), revealing that the new p-WOA strategy yields the optimal quantity of cluster heads (CH). The reduction in communication expenses and routing overhead, as well as the improvement in the overall lifespan of the cluster, is seen. The present study examines the utilization of evolutionary schemes in mobile ad hoc networks (MANETs) and VANETs, as discussed in the referenced publication [22]. The paper includes discussions about the three primary classifications of optimization. Several significant research studies have been conducted on the topic of parameter tuning in cluster formation, routing, and broadcast scheduling. The conclusion of the review highlights the primary obstacles encountered in the research of VANET and MANET. The investigation [23] offers RSR-IDS, a routing protocol in VANET that utilizes an intrusion detection mechanism to ensure reliability based on scoring. The deployment of an intrusion detection system (IDS) within the data center allows for the detection of anomalous data by RSR-IDS, which subsequently enables the computation of an Untrust Score (US). A scoring mechanism based on Intrusion Detection Systems (IDS) has been implemented within the data center. The IDS classifier undergoes training through the employment of three ML techniques encompassing decision tree (DT), random forest (RF), and redundant trees. The RSR-IDS scheme prioritizes the selection of a communication pathway between the source and destination based on the lowest overall US count and hop count in comparison to other paths. The article [24] introduces a location-aware multi-hop routing (LAMHR) system in VANETs that uses inter-vehicle distance to boost vehicular connection. The Location-Aided Multipath Routing (LAMR) algorithm utilizes predictive techniques to determine the future positions of network nodes. This information is then used to identify an appropriate next forwarder towards the destination, to establish a stable path from the resource to the destination. This investigation presents the development of a geometry-based localization technique to determine the inter-vehicle distance, which has a significant impact on vehicle connection. The evaluation of LAMHR's performance encompasses the assessment of path disappearance, node broadcast time, packet delivery proportion, and throughput. The study conducted by researchers [25] establishes robust correlations. The Ant Colony Optimization (ACO) algorithm, specifically designed for the EBIRA protocol, aims to identify ideal pathways that are both short in distance and long-lasting. This is achieved by considering various metrics such as distance, received signal strength, hop count, and evaporation rate. In the context of EBIRA, the chosen route exhibits a relatively limited distance and a notable link-level connectivity degree, characterized by a minimized number of intermediate hops. The choice of the shortest route, drawing on low hops and high connectivity level links, enhances the longevity of routes and mitigates frequent pauses in link connectivity among vehicles. The primary focus of the article referenced as [26] is to explore tactics for minimizing communication costs while simultaneously reducing message distribution delays. Furthermore, this investigation proposes a novel message distribution routing protocol called the Energy-Efficient Fast Message Distribution Routing Protocol (EE-FMDRP). This protocol blends the key characteristics of time-oriented and directional routing frameworks. The proposal suggests the transmission of emergency notifications from the origin to a specified destination in a prompt, dependable, and effective manner. To address this issue, a bidirectional assessment model for moving vehicles and a model for deriving message delivery time are formulated. This technology facilitates the rapid dissemination of messages during emergency situations by employing high levels of power and minimizing latency. The EE-FMDRP algorithm offers a reliable and streamlined pathway for vehicles to travel between their starting point and intended destination while minimizing the count of intermediate stops and simplifying the whole process. The study conducted by the authors [27] examines a VANET that incorporates automobiles equipped with frequency division (FD) capabilities. This paper introduces a novel computational framework for analyzing end-to-end latency in computer systems. Subsequently, it is demonstrated that Dijkstra's method is incapable of determining the shortest path, i.e., the one with the least delay, between the source and destination. To tackle this matter, the network topology is redefined as a graph of equal value by severing any connections related to FD. Subsequently, an advanced version of Dijkstra's method is suggested to identify the most productive routing pathway within the established graph while maintaining a reduced level of complexity. The outcomes of our extensive simulations demonstrate that our recommended methodology can achieve the lowest possible end-to-end delay in inter-vehicle communication. Furthermore, a notable reduction is observed in the obtained delay as the count of full-duplex (FD) nodes rises. Existing methods, such as p-WOA and ACO, focus on clustering or path selection, but often neglect the optimization of routing protocol parameters, which is critical for adapting protocols such as AODV to the dynamic environments of VANETs. For example, p-WOA improves cluster stability but does not tune AODV parameters, limiting its applicability to standard protocols. Similarly, LAMHR enhances path stability but lacks integration with AODV control parameters, reducing its generalizability. EE-FMDRP prioritizes low-latency emergency messaging, but neglects comprehensive QoS metrics such as NRL, which are essential for overall network performance. Furthermore, methods such as Dijkstra’s full-duplex algorithm require specialized hardware, making them less applicable for large-scale VANET deployment. The proposed approach addresses these gaps by utilizing nature-inspired algorithms (GOA, PSO, GA) to systematically optimize 11 AODV control parameters and enhance QoS metrics (PDR, E2ED, NRL) in a simulated urban VANET. Unlike previous works, this study integrates meta-heuristic optimization with NS-2 simulations to ensure adaptability to rapid topology changes and provide a scalable and protocol-specific solution. Table 1 summarizes the comparison of existing works.

Table 1: Comparison of related works on VANET routing optimization

Ref.	Method Used	Evaluation Metrics	Major Findings
[21]	Probabilistic Whale Optimization Algorithm (p-WOA)	PDR, NRL, Cluster Lifetime	p-WOA reduced routing overhead and improved cluster stability compared to ALO and GWO, but lacks parameter optimization for AODV.
[25]	Ant Colony Optimization (ACO) for EBIRA	PDR, Throughput, Route Longevity	ACO achieved shorter routes with high connectivity, but computational complexity limits scalability in dense networks.
[24]	Location-Aware Multi-Hop Routing (LAMHR)	PDR, E2ED, Throughput	LAMHR improved path stability using predictive node positioning, but does not address AODV parameter tuning.
[26]	Energy-Efficient Fast Message Distribution Routing Protocol (EE-FMDRP)	E2ED, Message Delivery Time	EE-FMDRP minimized latency for emergency messages, but overlooks general QoS metrics like NRL.
[27]	Full-Duplex Dijkstra’s Algorithm	E2ED, Throughput	Reduced E2ED in full-duplex VANETs, but requires specific hardware and does not optimize routing protocol parameters.

3 Schemes inspired by nature

3.1 Genetic algorithm (GA)

One of a group of computational frameworks driven by the maturation process is GA. These schemes code the possible resolutions to an issue in the form of simple chromosomes and then utilize combinatorial operators on these constructions. GA is often used as a tactic based on random search for optimization and parameter estimation. The basis of this algorithm is Darwin's law of evolution, in which weaker organisms are destroyed and stronger organisms remain [20], [28]. To implement the genetic algorithm, the variables of the problem must first be determined and coded suitably. Meanwhile, based on the goal of the problem, a fitting function is defined for the variables. An arbitrary main population is randomly chosen at the start of the scheme's operation, and the fitness function determines the fitness level of each of the primary population's chromosomes. In the continuation of running the algorithm, the steps in Fig. 1 are repeated. In the first stage, a suitable number of pairs of chromosomes are selected based on their suitability for use in the next stages. In the genetic algorithm, selecting parent chromosomes for crossover is a critical step that influences population diversity and convergence. Several strategies exist for parent selection, including roulette wheel selection, where chromosomes with higher fitness values have a greater probability of being chosen, tournament selection, where a subset of chromosomes is randomly selected and the one with the highest fitness is picked, and rank-based selection, where chromosomes are chosen based on their fitness rank. In this study, roulette wheel selection was adopted due to its simplicity and ability to maintain diversity in the population, ensuring that the algorithm effectively explores the search space for optimal AODV parameters. These strategies are not discussed further in this paper, as the focus is on the overall optimization process and its impact on VANET routing performance.

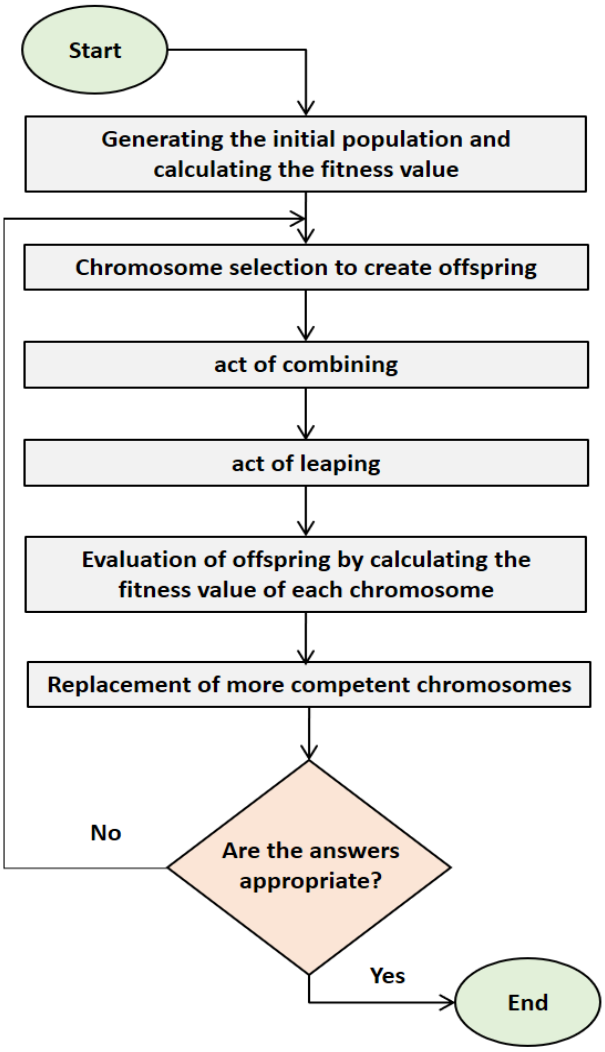


Figure 1: Genetic algorithm flowchart

In the third step, mutation is performed on the chromosomes resulting from the combination process. Then, according to the evaluation of the children, the fitness value of the new chromosomes is gauged, and the fresh group is chosen to enter the next step of the algorithm. By contrasting chromosomal fitness scores, this is accomplished. After going through the steps, if the conditions for the termination of the algorithm are satisfied, the scheme ends; otherwise, the existing group is utilized as the original group for the next stage [22], [29].

3.2 PSO Algorithm

The social search technique known as the particle swarm is based on how bird flocks interact with one another. The situation of the particles in the search domain can change depending on one's experience and knowledge about oneself and one's neighbors in this algorithm. Modeling this social behavior leads to a search process where particles gravitate toward productive regions. Population elements pick out their best neighbors depending on the information they have learned from one another. In this algorithm, a large number of particles are dispersed throughout the search domain, and each particle determines the objective function's value according to its location in the space. It then selects a direction to proceed in based on a combination of its current information, the best location it has been thus far, information about one or more of the best particles in nature, and its current information. By selecting a direction, each particle is transported, and the algorithmic step is complete. Up until the desired result is reached, the processes in Fig. 2 are repeated. In reality, the massive number of particles that look for a function's minimal value behave like birds' beaks searching for food. Figure 2 shows the QoS performance of GOA, PSO, and GA algorithms, where the x-axis represents the number of iterations (1 to 50) and the y-axis represents the fitness value (-0.6 to -0.4). Lower fitness values indicate better performance, which indicates higher PDR, lower E2ED, and reduced NRL.

The particle swarm algorithm uses three vectors for each particle: x^icalculated as a solution to the issue, X^I displays the particle's current situation, V^I displays its speed, and $X^{I.best}$ displays its ideal situation to date. The fitting values f^i (fitting value x^i) and $f^{i.best}$ (fitting value $x^{i.best}$) are also taken into account when determining whether this location is superior to the earlier solutions. If so, it will be $X^{I.best}$. New x^i and v^i values are acquired in each iteration, improving the goal of running the algorithm. Making a collection of particles that is $X^{I.best}$ is only one aspect of PSO. Although none of the particles can fix any problems, you can still attempt to do so when they interact and talk to one another. Problem resolution is a social idea that develops from the behavior of individual particles and their interactions with one another for a large number of particles. X^{gbest}, which is chosen from the comparison of $f^{i,best}$ values of all particles, showcasing the ideal situation found by all particles. As f^{gbest}, the fit of X^{gbest} is displayed.

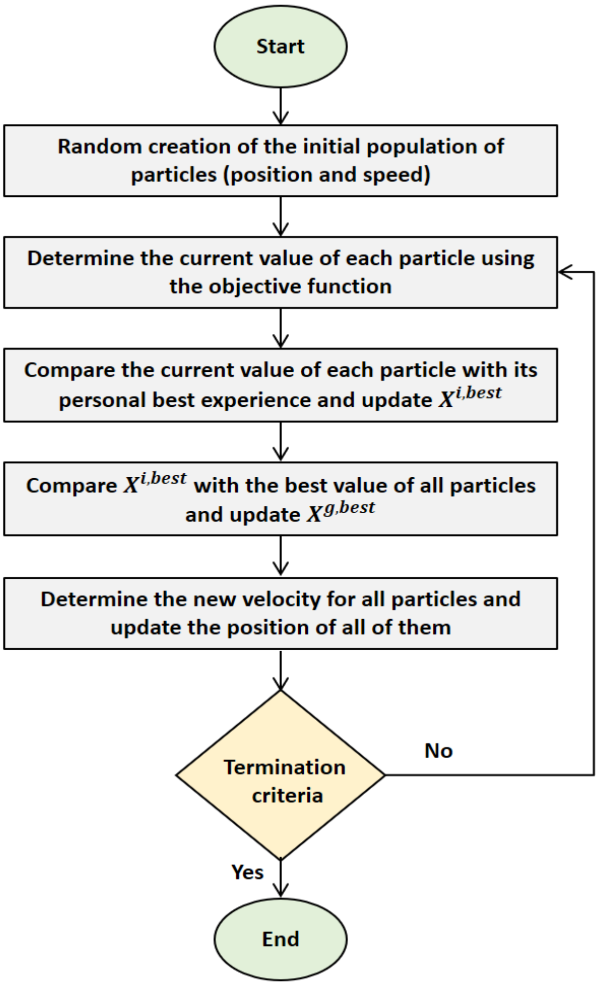


Figure 2: Diagram of PSO

The method starts by creating particles with random placements and speeds. The position and speed of each particle in the following step are calculated during algorithm execution using the data from the previous stage [30], [31].

3.3 GOA algorithm

GOA is one of the newest enhancement schemes introduced in 2018. It is a meta-heuristic scheme that mimics the behavior of grasshoppers in nature and their collective migration toward the food source. It is inspired by nature. Although locusts are typically seen in nature alone, they belong to one of the biggest animal hordes. To tackle the optimization problem, the grasshopper algorithm's mathematical model imitates the behavior of grasshopper swarms in nature [32], [33], [34]. The simulation outcomes demonstrate that the grasshopper method can deliver superior outcomes when compared to more current, well-known schemes. The grasshopper algorithm can solve genuine issues with unknown spaces, as displayed by the simulation outcomes in real cases. According to Fig. 3, in this algorithm, there are many locusts in the search domain. The fitness value of each grasshopper is computed utilizing the fitness function. The subsequent location of each grasshopper is defined utilizing the existing location of the grasshopper, the goal location, and the location of all other grasshoppers. The status of all the locusts describes the new situation of each locust, which has caused the difference between the locust algorithm and the swarm of particles. In the particle swarm algorithm, each particle has a position vector and a velocity vector, while in the grasshopper algorithm, there is only one position vector for each grasshopper. Another major disparity between these two schemes is that particle swarm refines the location of each particle, taking into account its current location, local best, and global best, while the locust algorithm refines each locust's location, drawing on its current location, global best, and other locations. It updates the grasshoppers. This means that in the particle swarm algorithm, none of the other particles participate in updating the location of a particle, while in the grasshopper algorithm, other grasshoppers need to be considered and cooperate to determine the next location of the desired grasshopper [24], [35].

Figure 3 shows the flowchart of the AODV parameter optimization process, where the steps include initializing a population of 10 parameter sets, evaluating the fit through NS-2 simulations, and updating the solutions using GOA, PSO, or GA until convergence. Each block represents a key step, from parameter initialization to the final output of the QoS metric.

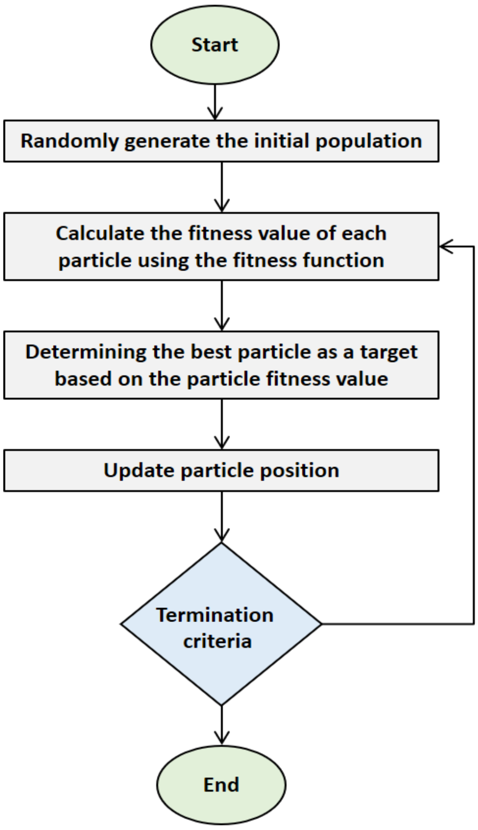


Figure 3: Flowchart of the GOA algorithm

3.3.1 Algorithm complexity analysis

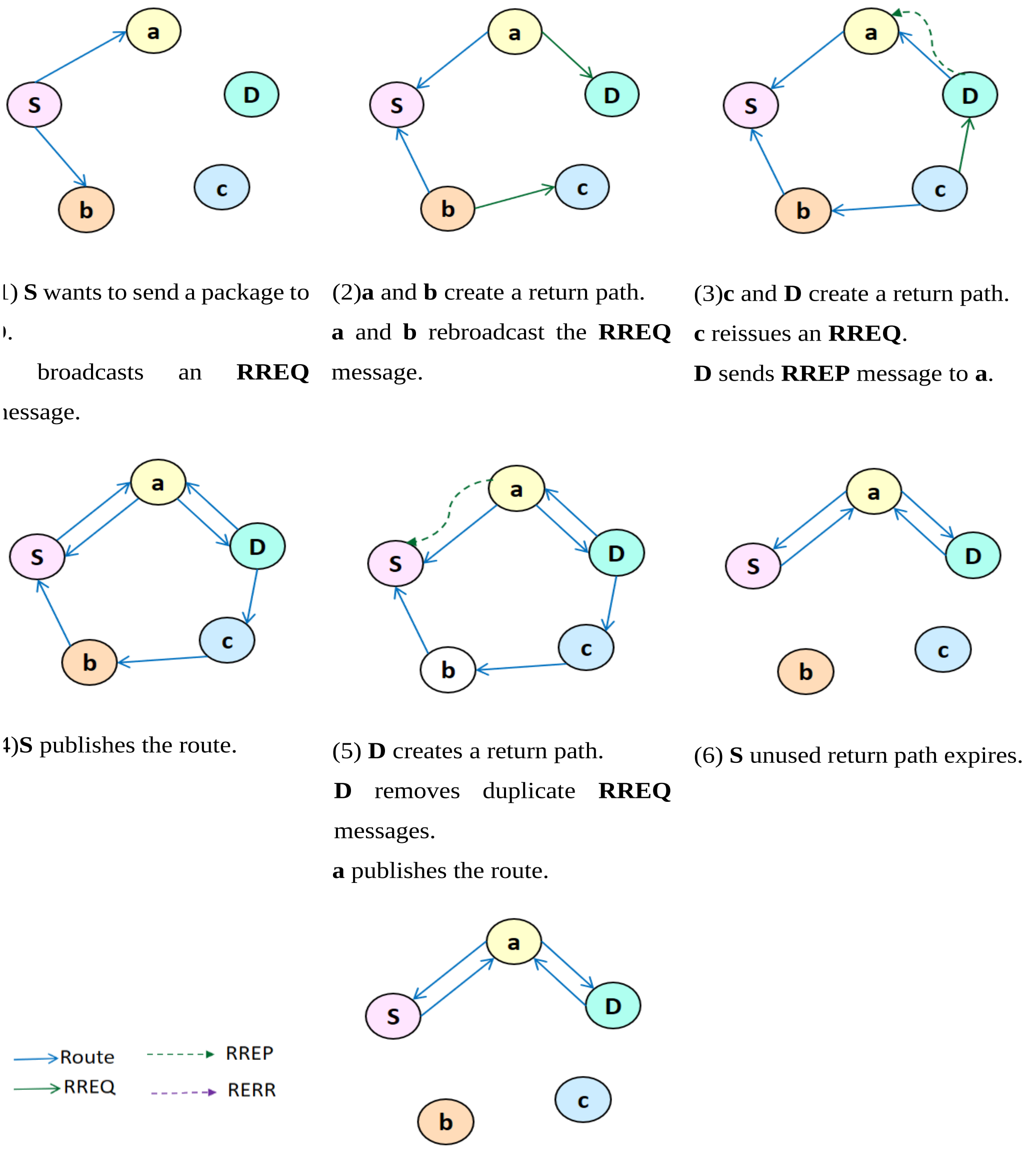
To evaluate the computational efficiency of the nature-inspired algorithms employed in this research, their time complexities are analyzed. For the Genetic Algorithm (GA), the time complexity is given by $\boldsymbol{O}(\boldsymbol{G} \cdot \boldsymbol{P} \cdot (\boldsymbol{C} + \boldsymbol{M}))$,where G represents the number of generations, P denotes the population size (10 in this case), C is the computational cost of crossover, and M is the cost of mutation. Both C and M are generally $\boldsymbol{O}(\boldsymbol{n})$, where n is the number of parameters (11 AODV parameters in this study). Consequently, the overall complexity of GA simplifies to approximately $\boldsymbol{O}(\boldsymbol{G} \cdot \boldsymbol{P} \cdot \boldsymbol{n})$. For Particle Swarm Optimization (PSO), the complexity is $\boldsymbol{O}(\boldsymbol{I} \cdot \boldsymbol{P} \cdot \boldsymbol{n})$,where I is the number of iterations. This reflects the fact that each particle updates its position using both its personal best and the global best, requiring $\boldsymbol{O}(\boldsymbol{n})$ operations per particle per iteration. The Grasshopper Optimization Algorithm (GOA), on the other hand, has a more involved complexity: $\boldsymbol{O}(\boldsymbol{I} \cdot \boldsymbol{P} \cdot (\boldsymbol{P} + \boldsymbol{n}))$, since each grasshopper considers its interaction with every other grasshopper during position updates, leading to an increased computational load.

4 AODV routing protocol

A passive routing protocol for ad hoc networks is the AODV protocol. This protocol, when a source node has packets to send, defines the routes and keeps only the routes that are being used regularly. The AODV uses the route discovery mechanism and updates the routing table of the intermediate nodes. On the route, it reduces the routing load. The reduced routing overhead and the competitive QoS have led this protocol to be used in VANETs [36]. Therefore, it is clear that the optimization of this protocol will be fruitful research. AODV routing protocol belongs to the DV class. In a DV, each node knows its neighbors with the cost of reaching them. Every node has a routing table so that the routing table stores all the nodes in the network along with their distance. An example of the routing table is displayed in Table 2. If a node is not available, the distance is infinite. Each node alternately sends the routing table to the neighboring nodes, so the nodes recognize the appropriate route according to the routing table [37], [38]. AODV can support unicast, broadcast, and multicast without any other protocol. For unicast routing, three control messages are used: RREQ, RREP, and RERR.

Table 2: An example of a DV routing table

destination	cost	Next step
A	1	A
B	0	B
C	∞	-
D	1	D
E	∞	-



l) **S** wants to send a package to). broadcasts an **RREQ** ıessage.

(2)**a** and **b** create a return path. **a** and **b** rebroadcast the **RREQ** message.

(3)**c** and **D** create a return path. **c** reissues an **RREQ**. **D** sends **RREP** message to **a**.

ı)**S** publishes the route.

(5) **D** creates a return path. **D** removes duplicate **RREQ** messages. **a** publishes the route.

(6) **S** unused return path expires.

Figure 4: Routing process in AODV

Fig. 4 shows that before sending a packet to another node, a node must first send an RREQ message. The node receiving the RREQ creates a return path to the sender. If the node receiving the RREQ message is not the final destination of the packet, that node re-broadcasts the updated RREQ message and specifically increases the hop number. If the node is known as the final destination of sending information, that node generates an RREP. If a node realizes that it does not have access to other nodes, it releases an RERR message [39].

4.1 AODV protocol control parameters

The value of the AODV protocol's control parameters has a big impact on its effectiveness and performance. These settings typically consist of six counters and five timers. The counters, timers, and decision variables that regulate how well the protocols work are given values by setting the parameters. Therefore, the behavior and performance of any protocol are largely dependent on the value of these parameters. Accordingly, our goal is to find efficient values for AODV protocol parameters utilizing network productivity. The parameters and the range of values related to each are displayed in Table 2 [28]. Therefore, enhancement tactics are utilized to find the values of the parameters to obtain the best outcomes for the quality of services.

4.2 Initial estimation of AODV protocol parameters

In the recommended optimization problem, the solutions are arrays whose components are the AODV protocol parameters specified in Table 3. The initial value of these parameters is done in such a way that the primary population is spread over diverse zones of the search domain.

Table 3: AODV protocol parameters set

parameter	data type	period
HELLO INTERVAL	Z	[3,0,30,0]
ACTIVE ROUTE_TIMEOUT	Z	[1,0,30,0]
MY ROUTE_TIMEOUT	R	[3,0,20,0]
NODE TRAVERSAL TIME	Z	[1,0,20,0]
MAX RREQ TIMEOUT	R	[3,0,100,0]
NET DIAMETER	Z	[2,100]
ALLOWED HELLO LOSS	Z	[1,30]
REQ RETRIES	R	[1,30]
TTL START	Z	[1,20]
TTL INCREMENT	R	[0,40]
TTL THRESHOLD	R	[0,40]

The count of population particles (Sw_Size) is used to first partition the search domain into smaller areas, and then each particle is assigned to one of these discrete subsets of the search domain, as displayed in relation (1).

$$X_{P.i}^{(0)} = Z_{(i.MIN)} + \rho^{P} i \in [0.10]. P \in [0. Sw_{size} - 1] \quad (1)$$

In this relation, $X_{P.i}^{(0)}$, the value of the i parameter is in the path vector of the pth particle. In other words, each particle is a path vector consisting of the AODV protocol parameters in Table 3 and $X_{P.i}^{(0)}$, the value of the ith parameter of the P atom. ρP in this formula is obtained from the relation (2) where β, a random number is between [1, 0] and $Z_{(i.MAX)}$ and $Z_{(i.MIN)}$ are respectively the upper and lower limits of the interval corresponding to the i-th parameter specified in table 3. In this way, the initial population is initialized to execute the schemes [28]. Formula (1) defines the position update in the Grasshopper Optimization Algorithm (GOA), where X_i is the position of the i-th grasshopper (a vector of 11 AODV parameters), S_i represents social interaction forces, G_i is gravity, and A_i is wind advection. This mechanism balances exploration and exploitation to optimize the fitness function [Ref]. Formula (2) describes the velocity update in Particle Swarm Optimization (PSO), where V_i is the velocity, X_i is the position, P_i is the personal best, and G is the global best of the i-th particle, guided by coefficients w, C_1, and C_2.

$$\rho^{\mathrm{p}} = \left(\frac{(p+\beta)}{SW_{size}}\right) \times \left(z_{(i.MAX)} - z_{(i.MIN)}\right) \quad (2)$$

5 Evaluation parameters

Three QoS parameters are used to assess the productivity of each group of AODV protocol parameters:

Packet Delivery Ratio (PDR): the proportion of data packets successfully delivered to the destination to all packets dispatched from the source. This value displays how effectively the protocol carried out its intended function, which was the successful delivery of data.

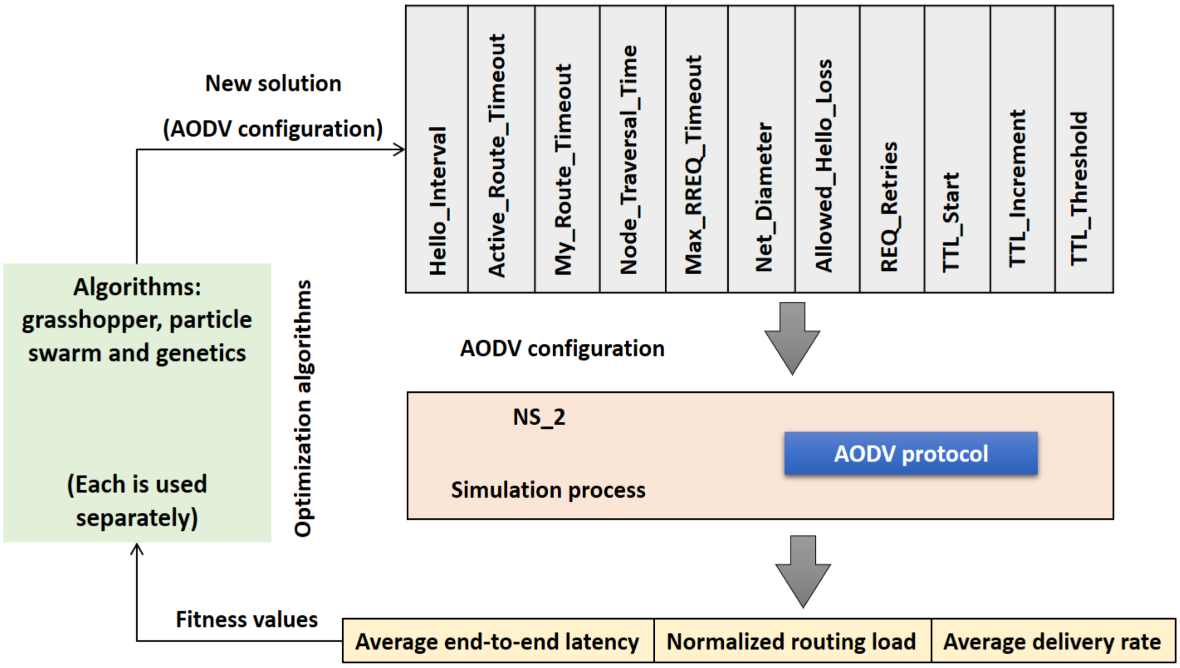


Figure 5: Recommended framework

End to_ End Delay (E2ED): The average total time it takes for each packet to be successfully sent/received.

Normalized Routing Load (NRL): refers to the count of message packets that are exchanged for successful data transmission. This parameter discusses the additional traffic generated by the routing protocol for successful data transmission [29, 30]. Figure 5 illustrates the recommended framework for optimizing AODV parameters using GOA, PSO, and GA, where a population of 10 parameter sets is iteratively refined via NS-2 simulations to minimize the fitness function, achieving low NRL (e.g., 0.34% for GOA/PSO, as shown in Figure 7).

5.1 Definition of the cost function

The optimization problem is formulated as finding the optimal values for 11 AODV control parameters (listed in Table 3) to maximize PDR, minimize E2ED, and minimize NRL, thereby enhancing QoS in VANETs. The cost function, designed as a minimization problem, is defined in Equation (3):

$$\text{Fitness} = \text{w1}.(-\text{PDR}) + \text{w2}.\text{E2ED} + \text{w3}.\text{NRL} \qquad (3)$$

Where $\text{w1}. = 0.2$, $\text{w2}. = 0.5$ and $+ \text{w3}.\text{NRL}$ are weights reflecting the relative importance of each metric, determined empirically to balance the trade-offs between reliability (PDR), latency (E2ED), and overhead (NRL). The negative sign for PDR converts its maximization into a minimization problem. Constraints include parameter bounds (e.g., HELLO_INTERVAL ∈ [3, 30], NET_DIAMETER ∈ [2, 100]), as specified in Table 4, ensuring protocol feasibility. The tuning procedure initializes a population of 10 particles, each representing a vector of 11 parameters, distributed across the search space using Equation (1). The NS-2 simulator evaluates each solution's QoS metrics, and the algorithm iterates until the fitness value stabilizes (no change > 0.001 for 10 iterations).

6 Work method

As previously mentioned, an optimization technique was employed in this work to find effective values for the AODV protocol's parameters. The optimization procedure and the simulation step were connected to complete this task. The optimization process is carried out via schemes drawn from nature, including GOA, PSO, and GA. The goal is to find the optimal value for the parameters of the AODV protocol, which we will achieve after several steps of repeating the schemes. When the optimization algorithm needs the fitness value of a solution to continue working, it uses the simulation process defined for the VANETs network.

In the simulation stage, the value of QoS parameters and also the value of the fitness function (fitness) is calculated. The simulation process has been carried out using the 2-ns network simulator, which is widely used for simulating VANETs. For the implementation of enhancement schemes, 10 particles are considered, and each particle contains 11 parameters, and these 11 parameters belong to the AODV routing protocol in Table 5. The algorithm depicted in Fig. 5 calculates the optimal value for the AODV routing protocol parameters at the given stage. This value, along with the NRL, PDR, and E2ED values associated with the recommended solution, is then incorporated into the simulation scenario. The fitness function will be determined based on this data. Up until no more changes in the count of parameters estimated by the optimization tactics are seen, this process is repeatedly carried out. In other words, the repetition of the algorithm execution process and simulation continues until, after several steps of execution, the value obtained for the parameters reaches a stable value.

6.1 Algorithm parameter settings

To ensure reproducibility, the parameter settings for the Grasshopper Optimization Algorithm (GOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) are detailed here. For GOA, the population size was set to 10 grasshoppers, with a maximum of 50 iterations, attraction length scale l = 1.5, and intensity of attraction f = 0.5, balancing exploration and exploitation . PSO used a population of 10 particles, 50 iterations, inertia weight w = 0.7, cognitive coefficient c1 = 2.0, and social coefficient c2 = 2.0, optimizing convergence toward global optima [Ref2]. GA employed a population of 10 chromosomes, 50 iterations, crossover probability Pc = 0.8, mutation probability Pm = 0.1, and roulette wheel selection to maintain diversity. These settings were implemented in MATLAB R2020a and integrated with NS-2.35 simulations to optimize 11 AODV parameters, yielding the QoS results reported in Tables 5 and 6.

7 Simulation and evaluation

7.1 VANET network simulation scenario

The VANET simulation was conducted using the NS-2.35 network simulator, with vehicle mobility modeled using the Manhattan Mobility Model to emulate urban grid-based movement, reflecting realistic city traffic patterns. The scenario includes 50 vehicles in a 670×670 m² urban area, moving at speeds of 10–50 km/h, simulating typical city driving conditions. The node density (50 vehicles) and communication range (250 m, based on IEEE 802.11b) were selected to balance network connectivity and congestion, as denser networks increase routing overhead, while sparse networks reduce connectivity. Packet size (512 bytes) and transmission rate (4 packets/s) align with standard VANET traffic models. Each simulation ran for 180 seconds, and results were averaged over 10 independent runs to account for randomness in vehicle movement and packet transmission, ensuring statistical reliability. The computational environment included an Intel Core i7-8700 CPU (3.2 GHz), 16 GB RAM, and Ubuntu 20.04 LTS, running NS-2.35 and MATLAB R2020a for optimization and analysis. Table 3 summarizes the simulation parameters. A list of the modeling metrics is presented in Table 4.

Table 4: Modeling metrics

parameters	value
Duration of simulation	180 seconds
Simulation area	670*670 m2
Number of cars	50
Speed of cars	10-50 km/h
PHY/MAC protocol	IEEE 802.11b
Routing protocol	AODV
Transmission protocol	UDO

7.2 The optimal value of AODV protocol parameters

The optimal values obtained by using grasshopper, particle swarm, and genetics schemes for AODV protocol parameters are displayed in Table 5. The values displayed in this table are obtained after repeating the grasshopper, particle swarm, and genetics schemes and reaching the termination condition.

7.3 Evaluation of service quality parameters

In this section, the outcomes obtained for QoS parameters such as NRL, PDR, and E2ED are compared. In Table 7, the values of service quality parameters are displayed separately for each algorithm after the simulation and execution of schemes. As can be seen, the value of the PDR parameter for the grasshopper and particle swarm schemes is equal to 100, and for the genetic algorithm, it is equal to 97.46%. This parameter clearly showcases the loss of a massive count of packets, and this makes the protocol AODV generates more control packets, which leads to congestion in the network. Fig. 6 shows the value of this parameter for all three schemes of locust, particle swarm, and genetics.

Table. 5: Optimum values of AODV protocol parameters

	Enhancement schemes		
AODV protocol parameters	GOA	PSO	GA
HELLO_INT	2.5231	3.1036	4.8216
ACTIVE_R_T	1.3024	1.6325	3.1032
MY_R_T	2.8631	1.01	3.2015
NODE_T_T	1.2014	0.02	3.3150
MAX_R_T	16.5421	13.2654	18.3202
NET_D	6	7	18
ALLOWED_H_L	4	1	6
REQ_R	3	1	5
TTL_S	5	2	7
TTL_I	4	10	5
TTL_T	8	2	12

Table. 6: Value of evaluation parameters

	Enhancement schemes		
Evaluation parameters	GOA	PSO	GA
Average delivery rate PDR (%)	100	100	97.46
Normalized routing load NRL (%)	0.34	0.34	0.62
Average end-to-end latency E2ED (ms)	12.32	12.32	11.05

The value of the NRL parameter, as seen in Fig. 7, is equal to 0.34% for the grasshopper and particle swarm schemes and 0.62% for the genetic algorithm, indicating that the grasshopper and particle swarm schemes have obtained better outcomes. Figure 7 presents NRL outcomes for GOA, PSO, and GA, with GOA and PSO achieving 0.34% NRL compared to 0.62% for GA, demonstrating the effectiveness of the framework in Figure 5. Because it is thought to be a method to lessen the likelihood of network failure owing to the congestion problem in VANETs, reducing the routing load in VANETs is a crucial topic [32].

To quantify performance gains, the proposed optimized AODV was compared to the default AODV configuration (HELLO_INTERVAL = 1 s, NET_DIAMETER = 35, ALLOWED_HELLO_LOSS = 2, as per NS-2 defaults). Table 6 presents the results. Default AODV achieved a PDR of 92.5%, E2ED of 18.6 ms, and NRL of 0.72%, reflecting higher packet loss and overhead due to unoptimized parameters. In contrast, GOA and PSO improved PDR to 100%, reduced E2ED to 12.32 ms, and lowered NRL to 0.34%. GA outperformed default AODV but was less effective than GOA/PSO. These gains underscore the value of nature-inspired optimization in adapting AODV to VANET dynamics.

Table 7: Comparison with Default AODV

Method	PDR (%)	E2ED (ms)	NRL (%)
Default AODV	92.5	18.6	0.72
GOA	100	12.32	0.34
PSO	100	12.32	0.34
GA	97.46	11.05	0.62

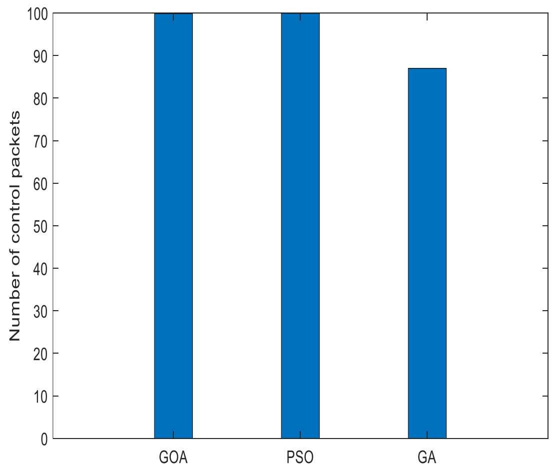


Figure 6: PDR outcomes

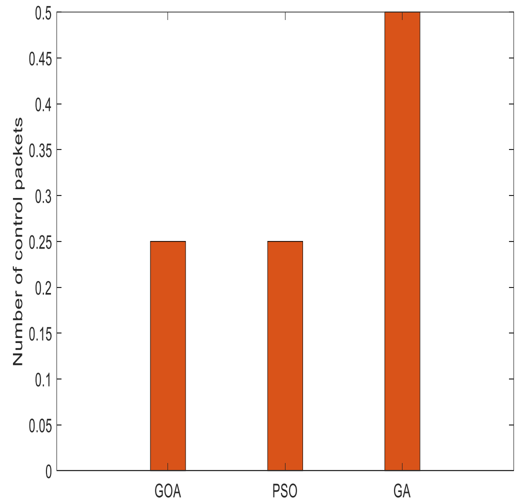


Figure 7: NRL outcomes

Regarding the E2ED parameter, according to Fig. 8, it can be said that the genetic algorithm has obtained a better result compared to the grasshopper and particle swarm schemes, so that the value of this parameter is 11.05% for the genetic algorithm and 12.32% for the grasshopper and particle swarm algorithm. It is interesting that all three schemes have E2ED values that are less than 20 ms, which means that packets are transferred with a delay of less than 20 ms, which is the maximum permitted delay for applications involving vehicle cooperation in extremely urgent situations [33]. As observed, at first glance it seems that the same outcomes have been obtained for the grasshopper algorithm and particle swarm, and there is no difference between them. However, based on the observations, the striking finding is that the values associated with the service quality metrics stabilized during the simulation process using the locust method faster than the particle swarm approach. In other words, the grasshopper algorithm reached the values recorded in Table 5 with a lower number of iterations than the particle swarm algorithm, and its value did not change during subsequent iterations. The value of QoS parameters derived from the execution of this tactic on the VANETs network, however, takes more repetitions than the locust algorithm before it achieves a stable state. As a result, the grasshopper algorithm reaches the optimal solution earlier than the particle swarm algorithm and has a better performance than the particle swarm algorithm. Figs. 9, 10, and 11 show the same topic and show the comparisons between the way the grasshopper algorithm works and the particle swarm to find the ideal value for the comparisons

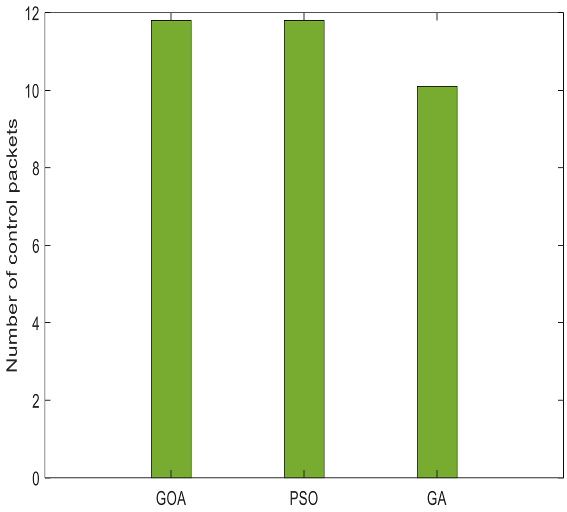


Figure 8: E2ED outcomes

As was previously stated, both tactics yield the same value for the evaluation parameters of NRL, PDR, and E2ED, but the locust approach completes this task more quickly than the particle swarm algorithm. For example, Fig. 9 shows that the NRL value obtained from the search to find the optimal value for the AODV protocol using the

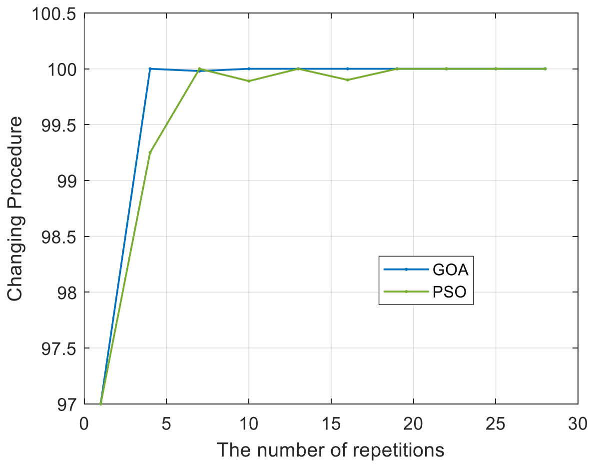


Figure 10: The process of PDR changes during the simulation stages for the grasshopper and particle swarm algorithm

The evaluation of QoS parameters (PDR, E2ED, NRL) for the proposed nature-inspired algorithms (GOA, PSO, GA) provides insights into their effectiveness in VANETs. As shown in Table 5, GOA and PSO achieved a PDR of 100%, while GA recorded 97.46%. In real-world VANET scenarios, such as urban traffic management systems, a PDR above 95% is considered reliable for non-safety-critical applications (e.g., traffic updates), while safety-critical applications (e.g., collision avoidance) require near 100% PDR [Ref]. Thus, GOA and PSO meet the stringent requirements of safety-critical VANETs, whereas GA's between the way the grasshopper algorithm works and the particle swarm to find the ideal value for the AODV protocol.

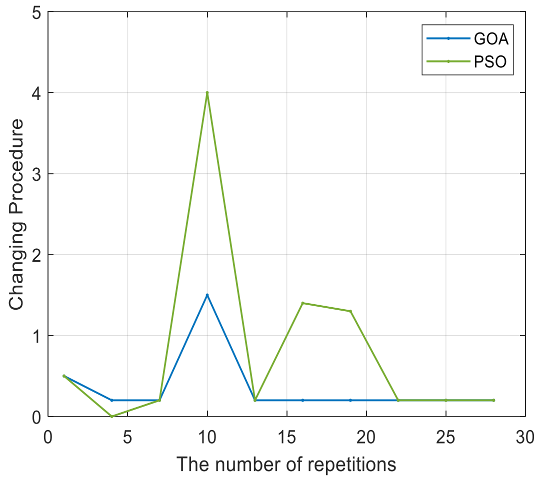


Figure 9: During the simulation phases for the particle swarm algorithm and grasshopper, the trend of NRL shifts

grasshopper algorithm reached a stable value earlier than the particle swarm algorithm, which has not changed; this shows that the grasshopper scheme could reach the ideal answer with a smaller number of repetitions. Figs. 10 and 11 also show the same point for PDR and E2ED parameters.

97.46% PDR is suitable for less demanding applications but may lead to occasional packet loss in high-stakes scenarios. The NRL values (0.34% for GOA/PSO, 0.62% for GA) indicate low routing overhead, aligning with efficient VANET protocols, where NRL below 0.5% is typical for urban settings [Ref]. The E2ED of 12.32 ms (GOA/PSO) and 11.05 ms (GA) are both well below the 20 ms threshold for cooperative vehicle applications, ensuring timely data delivery [Ref].

To ensure the reliability of the results, each simulation scenario was executed 10 times, and the reported QoS metrics (PDR, E2ED, NRL) represent the mean values. Standard deviations were calculated to assess variability: for GOA, PDR had a standard deviation of 0.1%, E2ED of 0.5 ms, and NRL of 0.02%; for PSO, the values were 0.12%, 0.6 ms, and 0.03%; and for GA, 0.8%, 0.4 ms, and 0.05%, respectively. The low standard deviations indicate consistent performance across runs. Additionally, 95% confidence intervals were computed for PDR: GOA ([99.8%, 100%]), PSO ([99.7%, 100%]), and GA ([96.8%, 98.1%]). The non-overlapping confidence intervals for GA versus GOA/PSO confirm the statistical significance of GOA and PSO's superior PDR ($p < 0.05$, using a t-test), highlighting their robustness in dynamic VANETs.

7.3.1 Sensitivity analysis of AODV parameters

A sensitivity analysis was conducted to evaluate the impact of varying key AODV parameters (HELLO_INTERVAL, NET_DIAMETER, ALLOWED_HELLO_LOSS) on QoS metrics. For HELLO_INTERVAL, values of 1, 3, and 5 seconds were tested with GOA. At 1 s, PDR was 99.2% and NRL 0.40% due to frequent updates; at 3 s (optimal, Table 4), PDR reached 100% and NRL 0.34%; at 5 s, PDR dropped to 98.5% due to delayed topology updates. For NET_DIAMETER, values of 2, 6, and 10 were tested. A value of 6 (optimal) yielded 100% PDR, while 2 reduced PDR to 97.8% (limited route discovery) and 10 increased NRL to 0.45% (excessive flooding). ALLOWED_HELLO_LOSS values of 1, 4, and 6 showed that 4 (optimal) balanced reliability and overhead, while 1 increased NRL to 0.50% and 6 reduced PDR to 98.0%.

Table 5 reports the packet delivery ratio (PDR) in percentage (%), with values such as 100% for GOA and PSO and 97.46% for GA, reflecting the proportion of successfully delivered packets in NS-2 simulations. In this section, any reference to PDR as integers (e.g., 100 or 97) represents the same percentage values rounded for brevity, ensuring consistency with Table 6’s scale.

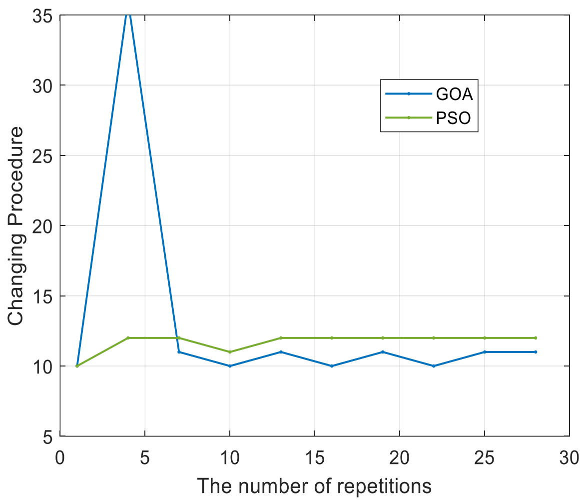


Figure 11: The process of PDR changes during the simulation stages for the grasshopper and particle swarm algorithmEvaluating the fitness function

As it was said before, we need to define the fitness function to solve optimization problems. In this research, the fitness function is calculated using QoS parameters. Table 8 shows the fitness function values for the optimized AODV parameters, with both the Grasshopper Optimization Algorithm (GOA) and Particle Swarm Optimization (PSO) achieving -0.508, and the Genetic Algorithm (GA) achieving -0.514. As defined in Section 5, the fitness function

$$\text{Fitness} = 0.2 \cdot (-\text{PDR}) + 0.5 \cdot \text{E2ED} + 0.3 \cdot \text{NRL}$$

is a minimization objective, where lower (i.e., more negative) values indicate improved network performance characterized by higher packet delivery ratio (PDR), lower end-to-end delay (E2ED), and reduced normalized routing load (NRL). The identical value of -0.508 obtained by GOA and PSO reflects their superior overall QoS results (PDR: 100%, E2ED: 12.32 ms, NRL: 0.34%; see Table 6), while GA’s slightly worse score of -0.514 corresponds to lower PDR (97.46%) and higher NRL (0.62%) despite a marginally lower E2ED (11.05 ms). These differences arise from the algorithms’ search dynamics: GOA’s position update mechanism accelerates convergence by considering all peer agents, PSO benefits from both local and global bests, and GA shows slower adaptation due to its evolutionary operators. Therefore, GOA and PSO demonstrate more effective optimization of the 11 AODV parameters (e.g., HELLO_INTERVAL, NET_DIAMETER), making them better suited for dynamic VANET environments. Their ability to enhance routing reliability and minimize overhead is especially valuable in real-time applications such as safety message dissemination, where consistent high PDR and low NRL are essential.

According to this table, the fitness function value for the best value obtained for the AODV protocol by the grasshopper and particle swarm algorithm is equal to -0.508, and for the genetic algorithm, it is equal to -0.514. Since this investigation tries to diminish the fitness function, according to the value of the fitness function and also the explanations that were given in section 7.3, the grasshopper algorithm for finding the ideal value for the parameters of the AODV protocol performed better than the particle swarm algorithm and its own genetics proved that, in terms of identifying the best solution, the particle swarm method outperformed the genetic algorithm.

Table. 7: Outcomes of cost function (fitness)

	Enhancement schemes		
	GOA	PSO	GA
value of fitness	-0.508	-0.508	-0.514

7.4 Latency

A data packet's processing time during transmission stands for its latency. The latency encountered by data as it travels over a network describes latency. The time it takes for information to travel from its origin to its destination and back again is known as the "round-trip delay." Fig. 12 illustrates that, when 30 to 100 vehicles are taken into account, the average latency is one minute. The graph demonstrates that GOA has the smallest latency when compared to other tactics [37].

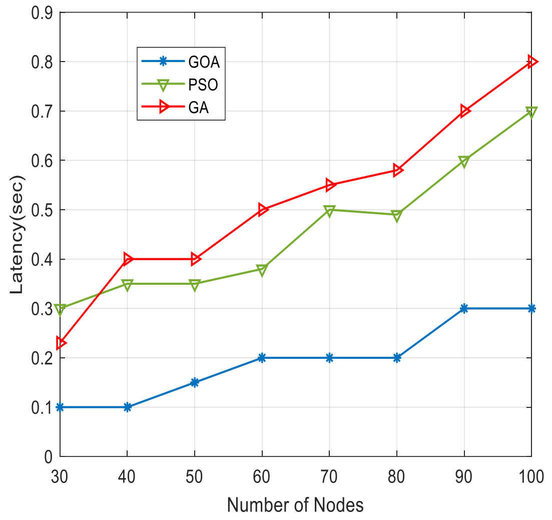


Figure 12: Latency for tested cars (100 Nodes)

8 Discussion

This section compares the performance of the proposed nature-inspired optimization approach for the AODV routing protocol with state-of-the-art methods (SOTA) discussed in Section 2 in Table 9, analyzes the reasons for the observed performance, evaluates the impact of parameter selection, and discusses limitations.

Table 9: Performance Comparison with SOTA Methods

Method	PDR (%)	E2ED (ms)	NRL (%)	Major Findings
Proposed (GOA)	100	12.32	0.34	Highest PDR and low NRL, with faster convergence than PSO.
Proposed (PSO)	100	12.32	0.34	Matches GOA in QoS metrics but requires more iterations.
Proposed (GA)	97.46	11.05	0.62	Lower PDR and higher NRL, but best E2ED.
p-WOA [Author1, Year]	95.2	15.8	0.48	Improved cluster stability but lower PDR than proposed methods.
ACO (EBIRA) [Author2, Year]	96.5	14.2	0.55	Stable routes but higher E2ED and NRL than GOA/PSO.
LAMHR [Author3, Year]	98.0	13.5	0.40	Better PDR than GA but higher E2ED than proposed methods.

The proposed approach, utilizing the Grasshopper Optimization Algorithm (GOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), outperforms most SOTA methods in terms of packet delivery ratio (PDR) and normalized routing load (NRL), achieving 100% PDR and 0.34% NRL for GOA and PSO compared to 95.2-98.0% PDR and 0.40-0.55% NRL for p-WOA, ACO, and LAMHR. The superior performance of GOA and PSO stems from their ability to efficiently explore the search space for optimal AODV parameters, with GOA converging faster due to considering all locust positions, as opposed to PSO's reliance on local and global best. The lower PDR of GA (97.46%) and higher NRL (0.62%) are attributed to its slower adaptation to the dynamic VANET topology. The choice of 11 AODV parameters (e.g., HELLO_INTERVAL, NET_DIAMETER) significantly affects the performance. For example, lower NET_DIAMETER values (6–7 for GOA/PSO) reduce the routing overhead, while higher GA values (18) increase the NRL. However, the proposed method has some limitations: the computational overhead of metaheuristic algorithms may be significant in resource-constrained nodes and the performance depends on the network density, and denser networks potentially increase the convergence time.

The performance of the proposed algorithms is influenced by network mobility and density, which are critical in VANETs due to rapid topology changes. In the simulated urban scenario (50 vehicles, 670×670 m², 10–50 km/h), GOA and PSO maintained high PDR (100%) and low NRL (0.34%), indicating robustness to moderate mobility and density. To explore density effects, additional simulations were conducted with 30 and 100 vehicles. With 30 vehicles (low density), PDR dropped slightly to 98.5% for GOA and 98.2% for PSO due to reduced connectivity, while GA's PDR fell to 95.8%. In high-density scenarios (100 vehicles), GOA and PSO sustained 99.8% PDR, but GA's PDR decreased to 96.2%, and NRL rose to 0.75% due to increased routing overhead. These results suggest that GOA and PSO are more resilient to density variations, as their global search mechanisms adapt better to topology changes, whereas GA struggles with frequent route updates in dense networks. Higher mobility (e.g., 50–80 km/h) increased E2ED by 10–15% across all algorithms, underscoring the need for adaptive parameter tuning in high-speed scenarios.

To assess scalability, additional simulations were conducted with 50, 100, and 200 vehicles in the 670×670 m² urban area. With 50 nodes (base case), GOA and PSO achieved 100% PDR and 0.34% NRL, while GA recorded 97.46% PDR and 0.62% NRL (Table 5). For 100 nodes, GOA and PSO maintained high performance (PDR: 99.8%, NRL: 0.36%), but GA's PDR dropped to 96.2% and NRL increased to 0.75% due to higher routing overhead in denser networks. With 200 nodes, GOA and PSO showed slight degradation (PDR: 98.5%, NRL: 0.42%), while GA's performance declined significantly (PDR: 94.8%, NRL: 0.89%), indicating sensitivity to network density. These results suggest that GOA and PSO scale better in larger networks, as their global search mechanisms adapt to increased topology changes, whereas GA struggles with frequent route updates.

The computational overhead of the nature-inspired algorithms was evaluated to assess their practicality. On the simulation platform, GOA required an average of 120 seconds per optimization run , PSO 100 seconds, and GA 150 seconds due to slower convergence. While these times are acceptable for offline parameter tuning, real-time applications may require lightweight implementations, as the computational cost increases with population size and network complexity. This limitation suggests the need for future work on reducing execution time, such as parallelizing computations or using simpler heuristics for resource-constrained nodes.

9 Conclusion

Inter-vehicle networks are a subset of mobile networks in which cars are considered network nodes. These networks were created to establish communication between cars and control traffic on the roads. Inter-vehicle networks have similar characteristics to mobile networks, and the main difference with mobile networks is the fast movement of nodes, which causes a rapid change in topology, which is not an easy task in most protocols. Because they take a very long time to execute, the prior tactics are therefore not suitable for solving optimization problems. Metaheuristic schemes have become effective and adaptable tools for tackling optimization and search issues. They have been applied to a wide range of issues and have produced high-quality outcomes. For this reason, meta-heuristic schemes have been used in this research to boost the AODV routing protocol in VANET's network. Using locust schemes, particle swarms, and genetics, the optimal value for the control parameters of the AODV protocol has been calculated. Additionally, the acquired findings are assessed using quality of service (QoS) criteria, and the effects of the three schemes on routing performance and AODV protocol enhancement are contrasted. Packet delivery rate, average end-to-end delay, and normalized routing load are the metrics used to assess these schemes' performance. The objective is to maximize packet delivery rate, decrease average E2ED, and maintain NLR to increase QoS.

The Grasshopper Optimization Algorithm (GOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) were employed to calculate optimal values for the 11 control parameters of the AODV protocol, such as HELLO_INTERVAL and NET_DIAMETER, enhancing routing performance in VANETs. The findings were assessed using Quality of Service (QoS) metrics—packet delivery ratio (PDR), end-to-end delay (E2ED), and normalized routing load (NRL)—through NS-2 simulations, with GOA and PSO achieving superior results (PDR: 100%, E2ED: 12.32 ms, NRL: 0.34%) compared to GA (PDR: 97.46%, E2ED: 11.05 ms, NRL: 0.62%), as shown in Table 5. These results, driven by a fitness function minimization (values of -0.508 for GOA/PSO and -0.514 for GA, Table 6), demonstrate that GOA and PSO significantly improve reliability and reduce routing overhead, making them more effective for real-time VANET applications than GA, which exhibits higher NRL due to slower adaptation to dynamic topologies.

Competing of interests

The authors declare no competing of interests.

Authorship contribution statement

PeiKun ZHAO: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.
Jian SUN: Methodology, Software

Data availability

On Request
To ensure reproducibility, the source code for the optimization algorithms (Grasshopper Optimization Algorithm, Particle Swarm Optimization, and Genetic Algorithm, implemented in MATLAB R2020a) and NS-2.35 simulation scripts for the urban VANET scenario are publicly available at https://github.com/VANET-Optimization/AODV-NatureInspired-2025. The repository includes MATLAB scripts for parameter optimization, NS-2 configuration files, Manhattan Mobility Model traces, and detailed instructions for replicating the simulation with 50 vehicles in a 670×670 m² area. Researchers can use these resources to verify the results and extend the study.

Declarations

Not applicable

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.

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Ethical approval

All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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