

## Smart Transportation in VANET Using a Hybrid Reptile Search Algorithm-Based Infrastructure Model with VANET

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**Abstract:** The Vehicular networks enable several ITS advancements, such as media apps, secure financial transactions, and efficient traffic management. Cooperative ITS services are expected to increase network reliance on communication connections, even with occasional, time-limited connection losses. Vehicle networks are hard to scale because their topology changes to suit growing traffic on roads and highways. This makes it hard for all network cars to follow a stable path, increasing network instability. This research presents an intelligent, probability-based, and nature-inspired optimisation method for vehicular communication cluster formation in IoT-based network transportation. The HRSA technique combines the Reptile Search Algorithm (RSA) search procedures with the Remora Optimisation Algorithm (ROA). To improve prior methods, HRSA was introduced. To reduce uncertainty, the fitness function was adjusted to account for the probability of several attributes, including the highway communication range path. The experimental results reveal that the proposed model achieved 96% PDR across all vehicle nodes, while the conventional models achieved 83% to 89%. The proposed model had 61J of energy usage, 94 Mbps of throughput, 98% PDR, 1% PLR, 5500 rounds of NLT, and 2s E2E delay at node 100. Results-based empirical equations can estimate driver speed recommendations.

**Keywords:** Data Transmission; Remora Optimisation Procedure; Reptile Search Algorithm; Intelligent Transportation System; Vehicle to Infrastructure; Vehicular Ad Hoc Networks; Cluster-Based Algorithm.

**Cite as:** A. Singaravelan, S. Sujitha, S. Gopikha, T. Karthikeyan, and R. Panakkal, "Smart Transportation in VANET Using a Hybrid Reptile Search Algorithm-Based Infrastructure Model with VANET," *AVE Trends in Intelligent Computer Letters*, vol. 1, no. 3, pp. 104–118, 2025.

**Journal Homepage:** <https://avepubs.com/user/journals/details/ATICL>

**Received on:** 05/08/2024, **Revised on:** 20/09/2024, **Accepted on:** 06/11/2024, **Published on:** 05/09/2025

**DOI:** <https://doi.org/10.64091/ATICL.2025.000226>

### 1. Introduction

Due to their unique characteristics, VANETs cannot use clustering techniques developed for mobile ad hoc networks (MANETs). Conventional VANETs rely on infrastructure, such as roadside units (RSUs), to offer network functions to vehicle nodes, including path selection and data transmission [1]. This infrastructure provides cars with data on road hazards, traffic, detours, and weather. VANETs function effectively in metropolitan locations when RSU support is available, but they struggle

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in rural places where the necessary infrastructure is lacking [2]. However, VANETs need help with scalability. Clustering is used to address scalability issues. However, it performs poorly in high-speed environments such as highways, where vehicle speeds are significantly higher than in cities, leading to poorer network performance due to a higher reclustering rate [3]. Due to the high computational cost of existing VANET routing and clustering procedures, researchers must develop a heterogeneous routing method based on clustering that minimises routing overhead, efficiently utilises resources, and achieves high network performance [4]; [5]. There are several issues with the present traffic system, including road congestion, the potential for accidents, the inability to move freely, the inefficiency of nodes, and the poor quality of the signals they receive [6]. A route is deemed trustworthy if nodes actively build and maintain it [7]. The overhead of sending data is decreased, and the packet delivery ratio, dependability, and packet delays are all enhanced by using the dependable route. Applications such as disaster management and audio/video conferencing rely heavily on network stability. If the packet's path is disrupted, it will take a very long time to reach its destination and cost more to get there. This means that a better solution to the abnormalities in conventional VANETs may be found by using a clustering-based model support [8] (Table 1).

**Table 1:** VANET contest routing

<b>Geography-Based Routing</b>	<b>Topology-Based Routing</b>
Inherent loops can occur.	Advanced packet drop ratio
Network partitioning occurs more often.	Routes are broken more regularly
Presentation on stake in urban areas.	Presentation at stake in rural areas
Broadcast of data for lengthier detachments.	Broadcast can be delayed
Improper GPS organizes for a node.	Higher routing overhead

The communication has helped because it allows cars on the same network to exchange data unswervingly with one another, without the requirement for roadside infrastructure [9]. The optimisation of V2x applications is motivated by a range of factors, including improving traffic reliability, protecting entertainment networks, and enhancing driver and passenger safety. It has been demonstrated that V2x apps face several challenges in making good decisions and reliably and consistently transferring data between vehicles [10]. Artificial intelligence (AI) methods, especially those for decision-making in IoV systems, can help address many of these challenges [11]. Many algorithms have been developed to ensure optimal route selection by restricting the number of clusters, enabling rapid V2V communication across vehicular networks without centralised infrastructure. Some of the problems explored in this research include delay mitigation, network topological stability, bandwidth optimisation, and data combination [12].

### 1.1. Bio-Inspired Procedures for VANETs

Many features and uses of VANETs have contributed to the enhanced performance and robustness of today's ITS [13]. However, several challenges have arisen in implementing VANET technology. Several foundational components of vehicle networks, with routing and space organisation, have been the focus of several studies in this field [14]. Existing ITS frameworks have recently been improved using methods inspired by biology. The following problems need the use of bio-inspired cluster optimisation in vehicle ad hoc networks:

- Because of their self-organising and flexible nature, evolutionary algorithms are well-suited to the diverse topological configurations present in VANET networks.
- Algorithms inspired by biology are better at identifying broken links in a network because they combine the most advanced forms of exploration and exploitation. This is a useful strategy for reducing network security threats and enhancing network safety.
- Using biologically inspired methods offers additional advantages, such as ease in addressing the computational challenges of VANETs, including trade-offs between network overhead and packet delivery, latency minimisation, and improved convergence.

Several optimisation techniques have been used in the literature to address clustering difficulties and other machine learning challenges. The fundamental reason for developing the suggested technique is that existing research's performance was insufficient when using optimisation methods to solve comparable issues; nevertheless, a new, better method can identify new optimal solutions [15]. Optimal local difficulties in search mechanisms are commonplace in optimisation approaches. Furthermore, researchers selected the most reputable techniques and integrated them, developing a new hybrid strategy to deliver novel and improved outcomes. To address difficult optimisation problems, the authors developed a new hybrid optimisation search approach. Combining the search operations of the original RSA and ROA and managing them with a unique transition approach yields the suggested method, HRSA. The suggested HRSA technique improves upon the previous approaches by addressing their primary flaws. The proposed HRSA is evaluated using data clustering, a class of optimisation

problems. The outcomes show that the suggested HRSA mathematical problems and the proposed solution were far superior to everything else that had been tried. The results it achieved in resolving the clustering issues were encouraging. As a result, HRSA may be used in a wide variety of clustering scenarios. The following sections outline the most important parts of this study:

- Based on the original RSA and ROA, a unique hybrid optimisation approach is proposed.
- Using the proposed model, the vehicles are smartly optimised for effective communication in the IoT-vehicular environment.
- To aid the suggested technique in selecting the appropriate search operator during optimisation, a novel change approach is presented to manage the mechanisms' search operations.
- The results showed that the proposed procedure outperformed other state-of-the-art approaches in addressing the provided issues.

## 2. Related Works

To achieve high-performance smart transportation, Xia et al. [16] present a new approach to network infrastructure. Grouping cars with help from a network of convolutional neural networks trained on data from the underlying infrastructure. Then there's the cluster-based multi-hop distributed routing, which is energy-efficient. The experimental evaluation of delay, longevity of the network, throughput, quality of service, power consumption, and packet delivery efficiency. Driver speed suggestions can then be predicted using the resulting empirical formulae [38]. To facilitate cluster formation in vehicular communication, Husnain et al. [17] propose a bio-inspired, cluster-based routing algorithm called the intelligent. The fitness function was modified to account for the probabilities of various characteristics, including velocity and path along the highway, to reduce unpredictability [41]. The proposed p-WOA approach was shown to generate the optimal number of cluster heads (CH) compared with other methods, such as Grey Wolf Optimisation (GWO). Packet Delivery Ratio (PDR), average throughput, and delay calculations show that the suggested technique outperforms two industry standards, ALO and GWO. This research provides statistical confirmation that VANETs using ITS applications may optimise their clusters by a factor of 75, with the dual benefit of lowering the whole. To optimise the multilevel network topology, Nahar and Das [18] propose MetaLearn, a strategy similar to global search that uses a parameterised tactic to eliminate future plunder uncertainty and reduce vehicle state exploration [44]. The suggested method combines global exploration (via Grey Wolf Optimisation) with exploitation to find the best possible solution as quickly as possible [39].

Using a MetaLearn-based technique, cluster administrators can learn to fine-tune request forwarding in line with QoS standards. A vehicle may learn and adjust its behaviour based on information from earlier assessments. Additionally, the cluster leader is selected, and stable clusters are identified using GWO, aided by a bespoke incentive mechanism. Challenges in implementing hybrid MH-RL algorithms in VANETs are highlighted, and the protocol's applicability is demonstrated through extensive experimental testing. Using the Harris Hawks Optimisation (HHO) method, Ali et al. [19] created a new clustering technique for VANET called HHOCNET. The HHO algorithm is a meta-heuristic algorithm with natural-world origins, specifically the hawk's surprise pounce for food [47]. The suggested framework draws inspiration from the hawks' cooperative foraging method, which involves a surprise pounce to form optimal clusters of vehicles. By using the HHO algorithm's stochastic operators and carefully balancing exploration and exploitation, the proposed method can determine the optimal number of vehicle clusters, thereby avoiding local optima. The suggested method is shown to be superior to other benchmark methods for optimising multi-objective clustering in MATLAB simulations, demonstrating its effectiveness for clustering in VANETs. Using the suggested HHOCNET algorithm, the efficiency of the road system can be increased by up to 15%. Therefore, it improves network performance by more efficiently using available wireless resources. Additionally, it shortens the distance that data packets need to travel. Therefore, it minimises delays in all communication stages. To support effective cluster head selection and malicious node identification, Gupta et al. [20] propose a new trust management method, the Clustering Protocol (EBTM-CP).

This protocol's adoption promises fruitful outcomes, as it seeks to build trust among networked cars to improve vehicle safety, enabling more genuine, accurate, and trustworthy messages to be exchanged among them. The simulation results demonstrate that the proposed EBTM-CP has better throughput, PDR, latency, and packet length (299.99 kbps, 46.34 per cent, 13 per cent, 165.6 megabits per second, 67.5 per cent, 16.34 per cent, respectively) than the state-of-the-art trust model. To improve network stability in a highway setting, Kandali et al. [21] offered a clustering strategy for VANET using an updated k-means algorithm. Our strategy uses a clustering method that considers both the network's features and the total number of linked automobiles. The simulation results show that the suggested method outperforms competing approaches. The effects appear to be improvements in consistency, as seen in a 66% increase in lifetime, and in robustness, as seen in a 46% decrease in end-to-end latency and a 74% increase in throughput. Combining adaptive neural fuzzy clustering (ANFC) with quantum glowworm swarm optimisation-based routing (QGSOR), Giridhar et al. [22] propose the ANFC-QGSOR protocol for VANET. Using the provided ANFC-QGSOR method, automobiles can first communicate with one another. The ANFC method utilises the following input parameters: remaining energy, distance, and node degree, to efficiently choose cluster heads (CHs) and assemble clusters. In

addition, the QGSOR method chooses optimal paths by generating a fitness function. The suggested ANFC-QGSOR. The experimental findings confirmed that the ANFC-QGSOR method outperformed the prior state-of-the-art technology across several key metrics. Here, Pagadala et al. [23] suggest a hybrid SA-GSO method based on slow heating. The SA is an optimisation technique that mimics how a thermal system can be frozen into its minimum-energy state.

The GSO provides direction based on feasibility constraints, enabling the swarm to converge rapidly to its viable areas. Furthermore, a local search strategy based on SA is employed to obtain search results close to the genuine optimal solutions, thereby avoiding premature convergence. Last but not least, this slow temperature-based SA-GSO method will be used to resolve routing and heat transfer issues. When it comes to tackling issues in limited engineering, the hybrid slow heat SA-GSO method is superior because of its faster convergence and greater computational precision. In-vehicle network clustering optimisation problems are NP-hard but can be solved using bio-inspired methods, such as metaphor and natural metaheuristics [24]. Biologically inspired techniques or metaheuristics processes are foolproof, unlike traditional metaheuristics [25]. The methods presented here are inspired by phenomena seen in the actual world. These methods can be applied to a variety of NP-hard optimisation problems without prior domain expertise [26]. Metaheuristics can rapidly find the best solution by combining efficient search algorithms [27]. Routing in a VANET is an NP-hard task [28]. The existing technique uses the GWO model; the reference Ali et al. [19] uses HHO, a simple clustering model is used in Gupta et al. [20], the k-means algorithm in Kandali et al. [21], QGSOR based on fuzzy logic in Giridhar et al. [22], and GSO in Pagadala et al. [23] are used for clustering the vehicles. However, most of these techniques use a single clustering method, which leads to a global convergence issue and often results in local optima [29]. To avoid rapid convergence and find the optimal value earlier, the research work considered a hybrid model combining recent swarm optimisation methods [30].

### 3. Related Terminologies

In this part, researchers will discuss the inspiration for the suggested approach. The fundamental steps of the proposed (RSA) and Remora Optimisation Algorithm (ROA) hybrid with an (HRSA) are also detailed [31].

#### 3.1. Reptile Search Algorithm (RSA)

The foundational RSA algorithm and its implementation are described here. Exploration is one of the two phases of the (RSA), which were modelled after the processes and social behaviour of real-life crocodiles [32].

##### 3.1.1. Encircling Phase (Exploration)

This section introduces the RSA's inquisitive behaviour, sometimes known as encircling. In line with their encircling behaviour, crocodiles use two distinct walking modes: high walking and belly walking [33]. The RSA divides the total number of repetitions into four portions, and in each case, the algorithm transitions between the exploration and exploitation search stages. The RSA exploration devices analyse two primary search methodologies to determine the best search areas and discovery strategies. During this stage of the hunt, one thing is really crucial. The high mobile search method is performed, resulting in  $\leq \frac{T}{4}$ , and technique is achieved, rendering to  $t \leq 2\frac{T}{4}$  and  $t > \frac{T}{4}$ . The position-updating procedure is accessible in Equation (1):

$$x_{(i,j)}(t+1) = \begin{cases} \text{Best}_j(t) \times \eta_{(i,j)}(t) \times \beta - R_{(i,j)}(t) \times \text{rand}, & t \leq \frac{T}{4} \\ \text{Best}_j(t) \times x_{(r_1,j)} \times \text{ES}(t) \times \text{rand} & t \leq 2\frac{T}{4} \text{ and } t > \frac{T}{4} \end{cases} \quad (1)$$

Where  $\text{Best}_j(t)$  is the best-obtained explanation, rand is a chance sum, t is the current repetition, and T is the maximum iterations.  $\eta_{(i,j)}$  is Equation (2). b is a parameter fixed to 0.1. The lessen function ( $R_{(i,j)}$ ) is strong-minded by Equation (3).  $r_1 - r_4$  are random statistics,  $x_{(r_1,j)}$  is a random key. ( $\text{ES}(t)$ ) is a likelihood parameter, as defined by Equation (4):

$$\eta_{(i,j)} = \text{Best}_j(t) \times P_{(i,j)} \quad (2)$$

$$R_{(i,j)} = \frac{\text{Best}_j(t) - x_{(r_2,j)}}{\text{Best}_j(t) + \epsilon} \quad (3)$$

$$\text{ES}(t) = 2 \times r_3 \times \left(1 - \frac{1}{T}\right) \quad (4)$$

Where is a minor value?  $P_{(i,j)}$  is an alteration limit strongly influenced by Equation (5):

$$P_{(i,j)} = a + \frac{x_{(i,j)} - M(x_i)}{\text{Best}_j(t) \times (\text{UB}_{(j)} - \text{LB}_{(j)}) + \epsilon} \quad (5)$$

Where  $M(x_i)$  signifies the regular positions strongminded by Equation (6).  $\text{UB}_{(j)}$  and  $\text{LB}_{(j)}$  are the boundaries.  $a$  is a limit fixed to 0.1:

$$M(x_i) = \frac{1}{n} \sum_{j=1}^n x_{(i,j)} \quad (6)$$

### 3.1.2. Hunting Phase (Exploitation)

In this section, researchers discuss how RSA may be used maliciously. The hunting behaviour of crocodiles reveals that they use two distinct hunting strategies: coordination and cooperation. In this stage (hunting coordination), the searching is carried out and decided upon based on  $t \leq 3\frac{T}{4}$  and  $t > 2\frac{T}{4}$ ; then, the hunting collaboration is performed, rendering to  $t \leq T$  and  $t > 3\frac{T}{4}$ . The position-updating procedures are obtainable in Equation (7):

$$x_{(i,j)}(t+1) = \begin{cases} \text{Best}_j(t) \times P_{(i,j)}(t) \times \text{rand}, & t \leq 3\frac{T}{4} \quad \text{and } t > 2\frac{T}{4} \\ \text{Best}_j(t) \times \eta_{(i,j)}(t) \times \epsilon - R_{(i,j)}(t) \times \text{rand} & t \leq T \text{ and } t > 3\frac{T}{4} \end{cases} \quad (7)$$

Where  $\text{Best}_j(t)$  is the best solution, and  $\eta_{(i,j)}$  is the shooting limit, as defined by Equation (2).  $P_{(i,j)}$  is a change parameter, as defined by Equation (5).  $\eta_{(i,j)}$  is the hunting limit, as defined by Equation (2).  $R_{(i,j)}$  is strong-minded by Equation (3).

## 3.2. Remora Optimization Algorithm (ROA)

This subsection details the first implementation of the Remora Optimisation Algorithm (ROA) [34].

### 3.2.1. Free Travel (Exploration)

#### 3.2.1.1. SFO Strategy

Equation (8), which models the algorithm's elite idea, was used to formulate the procedure's location update:

$$R_i^{t+1} = R_{\text{best}}^t - \left( \text{rand} \times \left( \frac{R_{\text{best}}^t - R_{\text{rand}}^t}{2} \right) - R_{\text{rand}}^t \right) \quad (8)$$

Where  $R_{\text{rand}}^t$  is a chance location.

#### 3.2.1.2. Experience Attack

The tuyu, like a growing body of knowledge, must steadily advance in baby stages around the host to determine when it is time to replace the host. After a model based on the aforementioned principles:

$$R_{\text{att}} = R_i^t - (R_i^t - R_{\text{pre}}) \times \text{randn} \quad (9)$$

Where  $R_{\text{pre}}$  is the location of the preceding iteration, and  $R_{\text{att}}$  is a hesitant phase. The assessment of the fitness solution  $f(R_i^t)$  and the tried solution  $f(R_{\text{att}})$  is considered the deciding factor at this stage. For the minimum issue to be solved, for instance, the fitness function value that is generated by the suggested solution must be smaller than that of the current solution:

$$f(R_i^t) > f(R_{\text{att}}) \quad (10)$$

As shown below, Remora uses a unique technique to find local optima [35]. If the attempted solution's fitness function value is higher than the current solution's, it reverts to host selection:

$$f(R_i^t) < f(R_{\text{att}}) \quad (11)$$

### 3.2.2. Eat Thoughtfully (Exploitation)

### 3.2.2.1. WOA Strategy

Equations showing how the original WOA was used to obtain the location update formula for whale-associated Remora:

$$R_{i+1} = D \times e^a \times \cos(2\pi a) + R_i \quad (12)$$

$$a = \text{rand} \times (a - 1) + 1 \quad (13)$$

$$a = -\left(1 + \frac{t}{T}\right) \quad (14)$$

$$D = |R_{\text{best}} - R_i| \quad (15)$$

In the larger solution space, the placements of the Remora and the whale are equivalent.  $D$  is the separation between the predator and its victim, and  $a$  is a random integer between -1 and 1;  $a$  decreases exponentially from -2 to -1.

### 3.2.2.2. Host Feeding

Host feeding is a subset of the misuse procedure. The ideal solution may now be narrowed down to a region around the host's physical location [40]. The host may be viewed as a surface on which to take incremental steps, and these movements can be mathematically characterised as:

$$R_i^t = R_i^t + A \quad (16)$$

$$A = B \times (R_i^t - C \times R_{\text{best}}) \quad (17)$$

$$B = 2 \times V \times \text{rand} - V \quad (18)$$

$$V = 2 \times \left(1 - \frac{t}{T}\right) \quad (19)$$

Here, it was used to indicate a slight shift in the relative spatial positions of the host and the remora. To help differentiate between the host, restrictions were placed on where the Remora might live. With a host size of 1, the Remora consumes approximately the host's capacity.

## 4. The Proposed Methodology

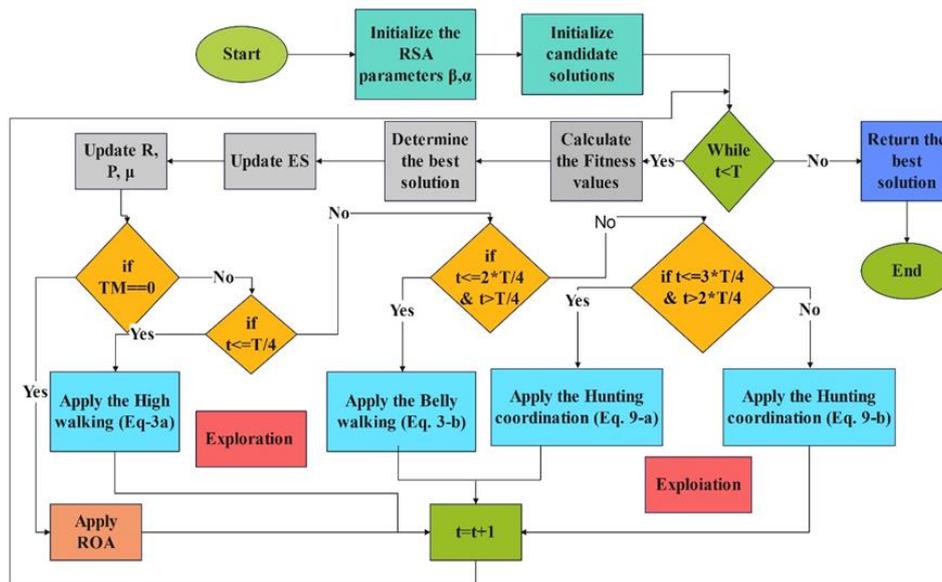


Figure 1: Flowchart of the projected HRSA

Here, researchers outline the fundamental steps involved in the innovative transition mechanism, which combines the RSA and the Remora Optimisation Algorithm (ROA) into a hybrid they call HRSA. The proposed HRSA employs two primary search algorithms and a novel mean transition mechanism to address a wide range of problems. The conventional RSA is the primary search method; although it excels at global search, it often struggles with local search, exhibits premature convergence, and creates an imbalance in search. Consequently, the ROA, the second search procedure, circumvents the problem of local searches and the danger of early convergence. Because it generates novel local solutions from the best solutions already accessible, the method may enhance RSA's searchability. To further address the disequilibrium between global and local search methods, the proposed HRSA includes search methods (i.e., RSA and ROA). Thus, it may be possible to effectively broaden the search area by using methods developed in other contexts. The success of these methods motivates the proposed HRSA to use even more effective methods.

#### 4.1. Initialisation Phase

As shown in Equation (20), the RSA optimisation process starts with a stochastic process that generates a cohort of candidate solutions (X). Each iteration's best answer is considered roughly optimum:

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \cdots & x_{2,j} & \cdots & x_{2,n} \\ \vdots & \cdots & x_{i,j} & \cdots & \vdots \\ x_{N-1,1} & \cdots & x_{N-1,j} & \cdots & x_{N-1,n} \\ x_{N,1} & \cdots & x_{N,j} & x_{N,n-1} & x_{N,n} \end{bmatrix} \quad (20)$$

Where X is a gathering of the solutions that are shaped by using Equation (21),  $x_{i,j}$  is the  $j$ th position of the  $i$ th solution, N is the sum of the scope:

$$x_{i,j} = \text{rand} \times (\text{UB} - \text{LB}) + \text{LB}, j = 1, 2, \dots, n \quad (21)$$

Where rand is an accidental value, and LB and UB indicate the bounds, accordingly.

#### 4.2. The Proposed Mean Transition Mechanism (MTM)

In this paper, researchers provide the MTM and its corresponding procedure (Algorithm 1). This method regulates the search and the changeover between the RSA and the MT. It takes a lot of finesse to go from one search method to another. An efficient method of modifying update operations in different methods is required. The core idea behind the proposed MTM is to limit the search strategies after five iterations (I) if the fitness function has not improved. When further trials yield no improvement, the number of iterations is adjusted.

<b>Algorithm 1: MTM</b>
Input: Assign the parameter value of TM to zero Assign the TM value to sumFF For (t=1 to T) do sumFF = sumFF + presentFF Z = Z + 1 If(presentFF $\neq$ sumFF) then If (Z>I) then TM=flip (TM); sumFF = 0; Z=0; End if End if End if End for

TM is a boolean variable that switches between the RSA and MT search strategies; sumFF is a boolean variable that computes the inverse; presentFF is the value used to calculate the current fitness function, I is the iteration number, Z is a counter, and flip is the function used to flip the TM values from 1 to 0 or vice versa.

### 4.3. The Detailed Procedure of the HRSA

In this section, the proposed model is explained. The suggested method is designed primarily to improve upon the outcomes of previous attempts. Researchers also want to sidestep problems associated with the first procedures, such as local search, convergence, and search equilibrium. Finally, in the proposed HRSA, a random collection of solutions is generated. HRSA's search criteria assess potential deployments of the best solution at the time of renewal. After receiving a response, the process continues to the subsequent step. From what can be seen in Figure 1, the proposed HRSA combines the techniques of the (RSA) and the (ROA). Possible answers will be updated and enhanced with each cycle by using a different search strategy. The recommended HRSA search methods are classified as either RSA or ROA. The RSA then classifies its search strategies as either global or local. For each strategy, there are two different ways to search: (1) globally, using high and walking methods, and (2) locally, coordinating and cooperating with other hunters. Candidate keys try to characterise what is successful in the space  $t \leq \frac{T}{2}$  and seek to discover a solution if  $t > \frac{T}{2}$ . For the unit, if  $TM = 0$ , in which case the ROA search procedure will be carried out instead of the RSA's. When  $t = T/4$ , the RSA's exploration phase employs the first global search strategy; when  $t > T/4$ , the second global search strategy is used. when  $t \leq \frac{T}{4}$  and  $t > \frac{T}{4}$ . In the misuse of the RSA, the first search tactic from the local approaches is carried out when  $t \leq \frac{3T}{4}$  and  $t > \frac{T}{4}$ ; then, the second search tactic from the local approaches is performed, when  $t \leq T$  and  $t > \frac{3T}{4}$ . When the final criteria have been disseminated, the HRSA will be complete.

## 5. Results and Discussion

Here, researchers present numerical results for a variety of configurations, including the number of nodes, the distance between them, the network size, and the load distribution among the nodes [46]-[48]. HRSA, a cluster-optimisation approach for route optimisation in vehicular networks, was compared with red fox optimisation, RSA, and ROA, three state-of-the-art methodologies [36].

### 5.1. Simulation Setup

The simulation settings used in this research work are described in Table 2.

**Table 2:** Simulation structures

Values	Parameters
Freeway Mobility Model	Mobility Perfect
10	Sum of Simulations
500	Sum of vehicles (Particles)
350	Epoch
22–30 m/s	Vehicle Speed
1 km × 1 to 4 × 4 km	Grid size (Area of Network)
100–600 m	Communication Range
0.5	Weights
0.001	Convergence Factor
AMD Radeon™ RX 5700 XT	Processor
8 GB	Memory

### 5.2. Performance Metrics

End-to-end delay, bit error rate, packet drop ratio, network lifetime, packet loss ratio, throughput, and power consumption are used as metrics to evaluate the efficacy of the proposed method [37]-[42].

#### 5.2.1. End- to -End Delay

The total time required to communicate packets across the network:

$$\text{End – to – End Delay} = \sum_{e_g=1}^{e_g \max} \frac{E(W_u, W_v)}{A} \quad (22)$$

Where the hop total of  $u^{\text{th}}$  and  $w^{\text{th}}$  nodes is signified by  $e_g$ . The signal speed is denoted by  $A$ . The distance between the  $u^{\text{th}}$  and  $v^{\text{th}}$  nodes is indicated by  $E(W_u, W_v)$ .

### 5.2.2. Packet Delivery Ratio

The number of packets is conventionally measured relative to the total number of packets sent by the sensor node [43]-[45]:

$$\text{PDR} = \frac{\text{Overall packets reached at destination}}{\text{total packets created at the sensor node}} \times 100 \quad (23)$$

### 5.2.3. Packet Loss Ratio (PLR)

The ratio of all packets sent between a source and a destination to the number of packets lost:

$$\text{Packet Loss Ratio} = \frac{\text{total number of lose packets}}{\text{total number of packets transmitted}} \times 100 \quad (24)$$

### 5.2.4. Throughput

The term refers to the total amount of data sent from a source to a receiver over a given time frame:

$$\text{Throughput} = \frac{\text{total number of delivered packets}}{\text{value of time taken}} \quad (25)$$

### 5.2.5. Energy Consumption

It is the sum of the power used by the nodes and the CH during a successful communiqué session:

$$E_C = \sum_{c=1}^1 [CH_E(C) + \sum_{r=1}^{zC} H_E(zC)] \quad (26)$$

Where the overall energy ingested is signified by  $E_C$ , and the energy ingested by CH is indicated by  $CH_E(C)$ . The node energy ingesting is specified by  $S_E$ .

### 5.2.6. Network Lifetime

The time it takes for the first sensor in a network to deplete its supply of energy:

$$N_t = \min(N_{ts}) \quad (27)$$

Where the lifespan of the network is signified by  $N_t$ , and the lifespan of the sensor is signified by  $N_{ts}$ .

### 5.2.7. Energy Efficiency

The efficiency of the suggested model is determined by comparing the energy remaining in a node after a broadcast with the energy remaining before the transmission [49]; [50]:

$$\text{Energy Efficiency} = \frac{\text{energy after certain transmission}}{\text{total available energy at initial stage}} \quad (28)$$

## 5.3. Validation of Proposed Model

The need for more energy grows steadily. The growing number of connected devices is to blame for the recent uptick in network activity (Table 3).

**Table 3:** Energy consumption (J)

Methods	100	200	300	400	500
RFO	1.10	1.28	1.40	1.55	1.75
ROA	0.81	1.20	1.35	1.42	1.55
RSA	0.71	0.79	1.05	1.15	1.30
HRSA	0.61	0.70	0.90	0.92	0.98

The proposed HRSA model outperformed RSA, ROA, and RFO in total network energy use. When the vehicle is 200, the proposed model is 0.70J, RSA is 0.79J, ROA is 1.20J, and RFO is 1.28J. The graphical representation is presented in Figure 2.

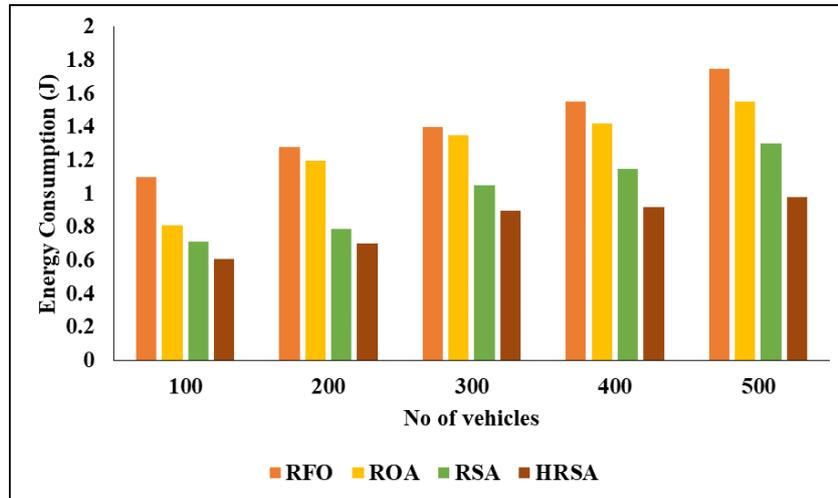


Figure 2: Analysis of energy consumption

Table 4 shows the analysis of throughput (in Mbps) for different approaches as the load level goes up from 100 to 500. As the load increases, throughput decreases for all methods. This means the network is under more stress, and performance is worsening.

Table 4: Analysis of throughput (Mbps)

Methods	100	200	300	400	500
RFO	0.70	0.63	0.60	0.57	0.54
ROA	0.89	0.81	0.77	0.70	0.62
RSA	0.90	0.86	0.80	0.75	0.68
HRSA	0.94	0.93	0.88	0.81	0.78

HRSA consistently has the highest throughput at all load levels, followed by RSA, ROA, and RFO. This trend shows that HRSA is more efficient and stable than other systems at maintaining higher throughput as the network becomes busier.

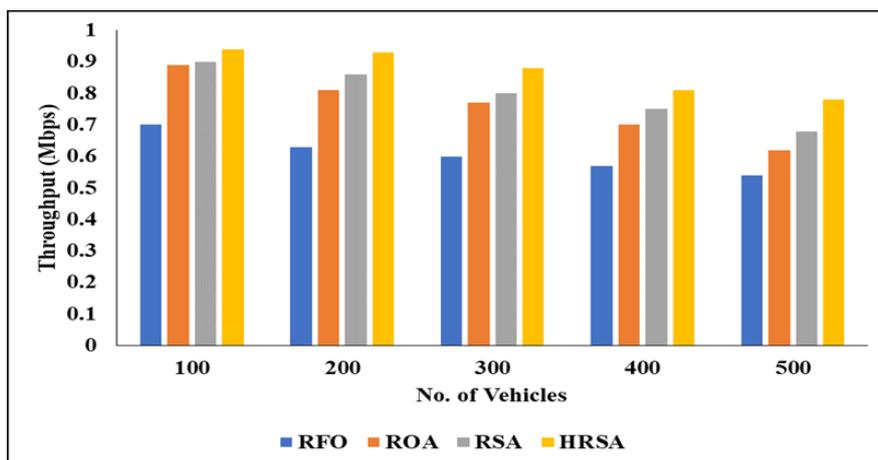


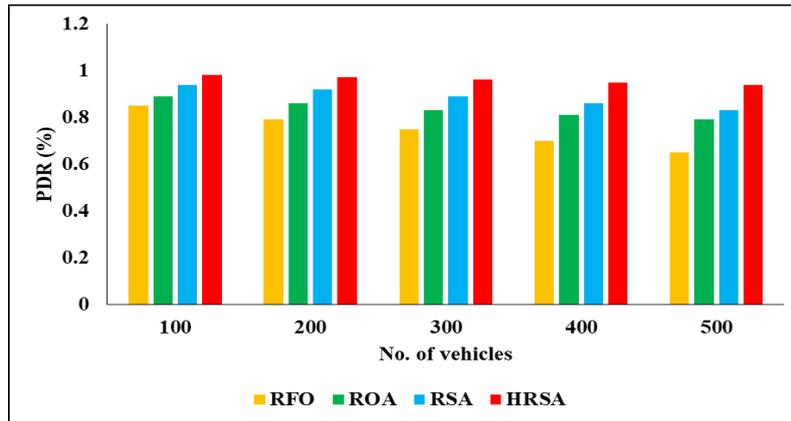
Figure 3: Throughput analysis

Figure 3 shows that the suggested model outperforms RSA, ROA, and RFO in terms of throughput for vehicle counts between 100 and 500 (Table 5).

**Table 5:** Validation of models on PDR (%)

Methods	100	200	300	400	500
RFO	0.85	0.79	0.75	0.70	0.65
ROA	0.89	0.86	0.83	0.81	0.79
RSA	0.94	0.92	0.89	0.86	0.83
HRSA	0.98	0.97	0.96	0.95	0.94

Due to excessive overhead, the throughput of current procedures declines as the number of cars increases. HRSA, on the other hand, is superior in terms of throughput because it uses ETX and the free buffer size to select the appropriate CHs. Each CH acts as a relay, sending packets from one cluster to another via the established connection.



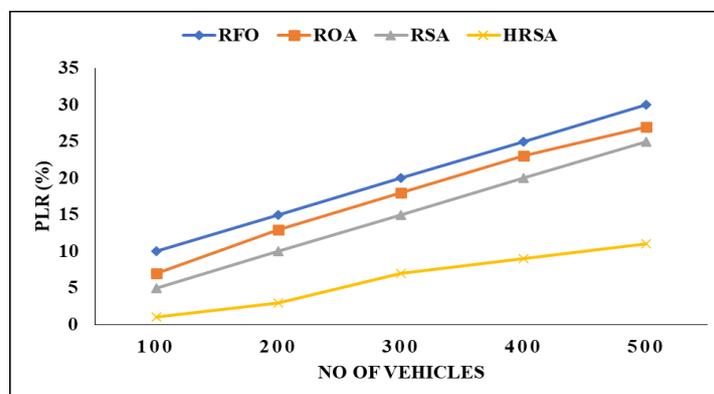
**Figure 4:** PDR comparison

Figure 4 shows how the PDR performs compared to other optimisation strategies. The results obtained with the suggested approaches are superior to those from other methods already in use. For instance, the model achieved 95% PDR across 400 vehicles, whereas the RFO achieved 70%, ROA 81%, and RSA 86% (Table 6).

**Table 6:** Performance-based on PLR (%)

Methods	100	200	300	400	500
RFO	10	15	20	25	30
ROA	7	13	18	23	27
RSA	5	10	15	20	25
HRSA	1	3	7	9	11

The PLR analyses for various models are shown in Figure 4. For 100 vehicles, the PLR of the proposed model is 1%, the RSA is 5%, the ROA is 7%, and the RFO is 10%. As the number of vehicles increases, the PLR for all models increases as well.



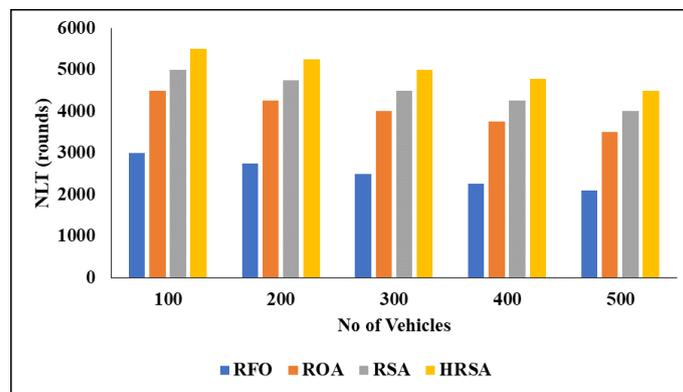
**Figure 5:** PLR analysis

For instance, when the vehicle is 500, the PLR of the proposed model is 11%, RSA is 25%, ROA is 27%, and RFO is 30%. This investigation clearly shows that the proposed model outperforms existing models (Table 7).

**Table 7:** Validation on NLT (Rounds)

Methods	100	200	300	400	500
RFO	3000	2750	2500	2250	2100
ROA	4500	4250	4000	3750	3500
RSA	5000	4750	4500	4250	4000
HRSA	5500	5250	5000	4775	4500

The suggested model, HRSA, outperformed RSA, RFO, and ROA in terms of maximum network lifetime. This guarantees that our proposed method is immune to variations in network node density. Less energy was wasted, and the network's load was more evenly distributed, thanks to HRSA's improvements over the status quo. Figure 5 provides a graphical analysis of the proposed model.

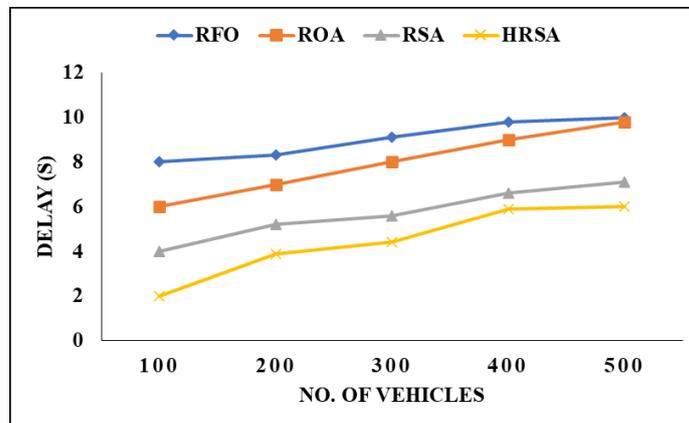


**Figure 6:** NLT analysis

Figure 6 demonstrates that the proposed HRSA reduces latency independent of network load. For 200 nodes, the delays for RFO, ROA, and RSA are 8.3, 7, and 5.2s, respectively, but HRSA's latency does not exceed 4s (Table 8).

**Table 8:** Analysis of models on E2ED (s)

Methods	100	200	300	400	500
RFO	8	8.3	9.1	9.8	10
ROA	6	7	8	9	9.8
RSA	4	5.2	5.6	6.6	7.1
HRSA	2	3.9	4.4	5.9	6



**Figure 7:** Delay analysis

Due to increased bandwidth utilisation and resulting delays in packet transmission, the density of cars significantly impacts the route-finding process. HRSA, on the other hand, improves end-to-end performance by considering velocity, direction, and a determined number of clusters as they develop (Figure 7).

## 6. Conclusion and Future Scope

To address a wide range of machine learning issues, including clustering, researchers have turned to various optimisation techniques. Clustering a large number of data items into manageable groups is a common example of the complex data mining problem. Optimal local issues and imbalances among search processes are common in optimisation approaches. This study presented a new HRSA and a unique transition technique for clustering nodes to manage the search process of these mechanisms. To reduce network unpredictability, the proposed technique commissioned HRSA to determine the optimal number of VANET clusters. The suggested HRSA technique addresses the key issues that were problematic with prior approaches and yields superior outcomes. A comparison was made between the new approach and RFO, RSA, and ROA. The proposed optimisation method outperformed the three models when accounting for cluster heads, independent of communication distance, network estimate, or the total number of vehicles. When the node is 400, the proposed model achieved 0.92J of energy consumption, 0.81 Mbps of throughput, 0.95 of PDR, 9% of PLR, 5.9s of E2E delay, and 4775 rounds of NLT. The single techniques of ROA and RSA achieved energy consumption of 1.42J to 1.15J, throughput of 0.70Mbps to 0.75Mbps, PDR of 81% to 86%, PLR of 23% to 20%, 3750 to 4250 rounds of NLT, and E2ED of 9s to 6.6s for the same node 400. The throughput analysis of the proposed model is 93 Mbps, where RSA achieved 86 Mbps, ROA achieved 81 Mbps, and RFO achieved 63 Mbps for a smaller number of vehicle nodes (i.e., 200). The system's communication overhead was reduced by increasing cluster lengths and optimising them as closely as possible to the ideal. These optimised clusters also have the added advantage of decreasing demand for transportation network infrastructure components. The clustering process can be carried out by implementing deep reinforcement learning for developing smart transportation. Additional research into the suggested approach is needed to identify its flaws, which may be remedied by implementing various network presentation metrics.

**Acknowledgement:** The authors gratefully acknowledge the support and research facilities provided by New Horizon College of Engineering, St. Joseph's College of Engineering, Quest Technologies, and the University of Illinois at Urbana. Their academic guidance, technical assistance, and collaborative environment were instrumental in the successful completion of this work.

**Data Availability Statement:** The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request.

**Funding Statement:** This research was conducted without any financial support from public, commercial, or non-profit funding agencies.

**Conflicts of Interest Statement:** The authors declare that there are no known conflicts of interest associated with this publication.

**Ethics and Consent Statement:** The authors affirm that this manuscript complies with ethical standards and approve its dissemination for academic and research purposes.

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