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Enhanced Ant Colony Optimization for Vehicular Ad Hoc Networks Using Fittest Node Clustering

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Abstract: Vehicular ad hoc networks (VANETs) are a rapidly evolving field at the intersection of intelligent transportation systems, emphasizing the need for a stable and scalable VANET topology to accommodate growing vehicular densities. The intricate challenge of route selection calls for advanced clustering protocols to bolster road safety and message routing. This research introduces a novel approach to intelligent clustering routing protocols, leveraging heuristic-based solutions built upon an enhanced ant colony optimizer (ACO) framework. The study unfolds in two stages: the creation of a dynamic search space model and the election of cluster heads (CHs). The innovative dynamic aware transmission range parallel Euclidean distance (DA-TRPED) technique establishes a dynamic search space using the parallel Euclidean distance (PED) concept. This approach evaluates vehicular nodes by estimating PED values, reducing the search process's complexity. Subsequently, an intelligent cluster head is selected by enhancing the dynamic evaporation factor (DEF) within the ACO technique. The experimental validation of the DA-TRPED technique takes place in NS2 simulations, demonstrating superior performance compared to conventional ACO. This enhancement is evident in metrics such as packet delivery, packet drop, throughput, end-to-end delay, and the lifetime analysis of clustered nodes. The proposed approach holds promise for optimizing VANETs, enhancing their stability and scalability while promoting road safety and efficient message routing.

Keywords: VANETs; ACO; DEF; parallel Euclidean distance; dynamic constraints; cluster head selection; search space modeling

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1. Introduction

Routing protocols and clustering techniques play essential roles in the operation of ad hoc networks, including mobile ad hoc networks (MANETs), vehicular ad hoc networks (VANETs), and flying ad hoc networks (FANETs) [1]. These networks require efficient routing to ensure reliable communication, and various intelligent approaches, such as fuzzy logic and artificial bee colony (ABC) optimization, can be used to enhance the performance of routing protocols. Let us discuss different routing protocols and how these intelligent approaches can be applied in the context of MANETs, VANETs, and FANETs [2]. MANETs include ad hoc on-demand distance vector (AODV), a reactive routing protocol that establishes routes only when needed, reducing overhead in the network, and dynamic source routing (DSR), a reactive protocol that maintains a route cache to store frequently used paths, reducing the latency in route discovery. VANETs are designed specifically for vehicular networks considering vehicle positions and speeds for routing decisions. FANETs require specialized routing protocols to account for the mobility and unique characteristics of flying nodes including protocols that consider altitude, 3D space, and dynamic network topologies [3].

VANETs have captured considerable attention from both researchers and the vehicular community. This type of network falls under the mobile ad hoc network (MANET) category, where vehicles are treated as communication nodes [4]. These vehicles employ transceivers to enable technologies, such as advanced driver-assistance systems (ADAS), the Internet of Things (IoT), and communication modes like vehicle-to-infrastructure (V2I), vehicle-to-vehicle (V2V), and vehicle-to-anything (V2X) [5–8]. The technology adheres to the IEEE 802.11p standards, facilitating the WAVE and DSRC models [6,9,10]. In this setup, vehicles collaborate using MANETs, resulting in dynamic and fast-paced communication that introduces significant challenges to the network structure. Consequently, the quality of service (QoS), including communication reliability, scalability, and quality, suffers. Various protocols have been proposed to alleviate the impact of poor inter-vehicular communication. However, achieving cooperation among deployed vehicular nodes remains complex. Intelligent clustering protocols have emerged to enhance network QoS substantially.

Routing protocols in ad hoc networks include non-clustering routing protocols and clustering routing protocols. Non-clustering routing protocols are based on a flat or peer-to-peer network structure and proactive (table-driven) or reactive (on-demand) route discovery mechanisms. Clustering routing protocols involve division of the network into smaller, manageable clusters, logically grouping vehicular nodes based on factors like communication links and node distances [6]. Clustering helps improve scalability by reducing the number of nodes participating in routing, which minimizes control overhead. Moreover, cluster heads can intelligently manage traffic within clusters, leading to better load balancing and improved network efficiency. In cluster protocols, control messages are confined to within clusters, reducing the overall control overhead in the network. In addition, clustering can provide better security and isolation within clusters, making it harder for external attackers to disrupt the network [11].

Clustering ant colony optimization (ACO) in VANETs is a technique used to address various optimization problems related to clustering in VANETs. Fuzzy logic and artificial bee colony (ABC) optimization can be applied to routing protocols in various ways to optimize the routing process in ad hoc networks. Fuzzy logic can be used to make routing decisions based on imprecise or uncertain network information considering factors like signal strength, link quality, and node mobility to make intelligent routing decisions. ABC optimization can be used to optimize routing parameters or adapt routing decisions dynamically based on network conditions through optimal routes by considering factors like energy efficiency, load balancing, and path reliability [11].

The clustering process operates based on specific criteria, each one defined by its application domain and functionality. The cluster network comprises cluster members (CMs) and cluster heads (CHs). Data are then transmitted through intra-cluster and inter-cluster processes [12]. The selection of cluster heads significantly influences network optimization. CHs facilitate high-speed data transfer, benefiting communication by enhancing the transmission capabilities and cellular interfaces of nodes under them. Thus, selecting CHs becomes a challenging task [9]. Addressing optimal clustering falls into the realm of NP-hard problems, often tackled with metaheuristic algorithms, as traditional clustering methods struggle to adapt across diverse communication scenarios.

Clustering in VANETs encounters challenges when handling dynamic network parameters, which can limit support for a wide range of vehicle routing applications. In our research, we believe we have achieved a significant milestone by introducing the dynamic aware TR-PED technique, effectively addressing the limitations of conventional swarm-based routing protocols. The key contributions of this paper are as follows:

- This study introduced DA-TRPED, a heuristic-driven clustering method that improves network connectivity and data delivery in heterogeneous environments (V2V and V2I) by incorporating dynamic transmission ranges into ACO. It also addresses the local search space problem through constraint modeling, promoting efficient collaboration and adaptability to changing topologies while reducing routing exploration time and congestion.

- We implemented the proposed DA-TRPED model to Network Simulator (NS-2) to facilitate the observation, tracking, and enhancement of the transmission process in comparison to traditional VANET models.

The remaining sections are organized as follows: in Section 2, we provide a comprehensive assessment of existing methods, highlighting their strengths and weaknesses. Section 3 outlines the research methodology, our proposed model and simulation criteria, offering insights into practical solutions for addressing the research challenges. Section 4 demonstrates the results of comparative simulated analysis to validate the effectiveness of the proposed communication model. Finally, in Section 5, we present the conclusions drawn from the proposed model and provide recommendations based on our findings.

2. Literature Review

Swarm intelligence represents a recent field that characterizes the behavior of distributed autonomous systems. Within the realm of vehicular networks, researchers investigate the communication and interaction between deployed vehicles and their environment through the lens of swarm intelligence [13]. This approach involves vehicles communicating directly, guided by factors such as architecture, speed, and light measurements. It mirrors the behaviors observed in natural phenomena like ant colonies, bird groups, fish schools, and microbial cognition. The challenges encountered during the transition phase of VANETs primarily revolve around ensuring stability and security in congested environments. Consequently, it is imperative to ensure connectivity in VANETs before practical deployment. The growing diversity within VANETs, with more vehicles equipped with onboard units (OBUs), enhances the likelihood of vehicular connectivity, thereby promoting fairness in vehicular communication modules [14]. Efficiently organizing reliable routing between deployed vehicular nodes is a task of great importance. Clustering emerges as an effective solution for designing efficient route planning processes and enhancing network stability.

In the context of VANETs, clustering can be categorized into two classes: network associativity-based and identifier-based algorithms [2]. The former focuses on selected cluster heads (CHs) and members within their nearest transmission range, while the latter operates in a manner similar to the CH with the least ID. In a study, it was noted that the connectivity-based model tends to perform less optimally than identifier-based algorithms [6]. In line with this observation, the CBRP algorithm was introduced, which optimizes the route planning process by transforming the lowest identifiers [15]. An ant colony system (ACS) was utilized for routing performance analysis [16]. Both the ACS and the ACS's variation algorithms have redefined challenges associated with clustering. However, the ACS's speed and accuracy have shown limitations. To address these limitations, ant colony optimization with different favors (ACODF) combines the selection of favorable ants with the stimulated annealing (SA) strategy, resulting in a faster path selection process [17]. This approach calculates node intensities, selects nearby nodes as ants, and utilizes a reactivation function based on pheromones. The cluster formation takes place at the edge points of the ant data. The ACS and its variation algorithm were applied to cluster data [18]. Similar studies, such as ant K-means (AK) and ant systems (ASCA), were conducted to address challenges related to clustering systems [19]. The combination of AK and ASCA was introduced to enhance the performance of database clustering models, with a focus on association rules algorithms and the continuous updating of pheromones using variance [20].

Moreover, trust-based ant colony routing (TACR) has been explored, considering parameters like vehicular nodes' position, direction, and relative speed [21]. To enhance the scalability of the clustering process, real-time updates of vehicle position and trust are taken into account. TACR was compared to the mobility aware-based DYMO algorithm, revealing the need to improve routing overhead in TACR compared to MAR-DYMO [22]. Conventional clustering architecture and ACO are employed to enhance the efficiency of routing operations, making ACO deployment beneficial for the VANET environment.

Various authors, as listed in Table 1, have explored the formulation of intelligent-based clustering models.

Table 1. Literatures of state-of-art clustering techniques in VANET applications.

Reference	Routing Application	Clustering Protocol	Performance Evaluation
[23]	Routing optimization	Whale algorithm	PDR, throughput, and overhead
[24]	True Pareto optimal	Dragonfly algorithm	PDR, throughput, and delay
[25]	Disconnections during communication	Firefly algorithm	Coverage
[26]	Capacitated vehicle routing problem	Grey wolf algorithm	PDR, throughput, delay, and degree of node
[27]	Rapid modulation in topology	Fuzzy bacterial foraging optimization	No. of clusters and grid size
[28]	Clustering formation	ACO and PCO algorithm	Simulation time and radio propagation
[29]	Geocast routing	PSO optimized	PDR, normalized routing load, and throughput

The advancement of VANET technologies has been utilizing the 5G network architecture for better network stability and connectivity. One study presented the software-defined network (SDN) on 5G communication systems to administer urban traffic [30]. The intention was to enhance repercussion time under the emergency scenario. A few parameters, such as vehicle localization, traffic forecasting, and control, were carried out by intelligent architectural design. An Internet of Vehicles (IoV)-based optimizer algorithm was introduced to support a dynamic routing system [31]. Adopting particle swarm optimization (PSO) and ACO for the routing development process proved that ACO has better efficacy than PSO in minimizing traveling time. A contact centric-based network (CCN) was introduced to eliminate the scarcity of IPs during transmission [32]. The concept of CCN-IoV in the CCN methodology was studied [33]. The performance of network delay and throughput parameters was not remarkable. The scalability of the IoV needs to be improved. Two metaheuristics-based algorithms also investigate the exploration of network performance using ACO in a VANET, comprehensive learning oriented PSO, and multi-objective PSO [34]. The study explored cost maximization for packet routing and minimized usage of cluster counts. However, the weights are static. In alignment with this, other parameters such as transmission range, mobility model, and topology are considered static. To summarize, the dynamic nature of evolutionary techniques can unleash interesting solutions to support large-scale networks. To further enhance the MOPs, the dynamic characterization of evolutionary algorithms have been incorporated. Several baseline algorithms, such as artificial immune system (AIS) [35], adaptive neuro-fuzzy interface system (ANFIS) [36], and genetic algorithm (GA) have been discovered [37]. Reinforcement learning maintains its effectiveness over time in finding the most optimal route in the VANET network [38]. An adaptive beaconing strategy based on the fuzzy logic scheme for geographical routing was investigated which effectively reduced the routing overhead and improved the packet-delivery ratio, throughput, average end-to-end delay, and normalized routing load as compared to traditional routing protocols [39].

ACO has resolved various optimization problems by proving its ability in solution discovery, better search strategies, and robustness. However, a few drawbacks are maximized, such as the time taken for searching, convergence speed, and stagnation of discovered solutions. The design of improved ACO will meet the following scenarios.

(a) Evaluating the communication stability under a dynamic nature.
(b) Estimating the fairness in network load distribution to have an optimized and scalable VANET environment.
(c) Evaluating the performance regarding packet delivery, throughput, and network delay to the number of vehicles and time.

3. Methodology

This section of the paper delineates the structure of our proposed ACO model and elucidates the underlying mechanisms, as illustrated in Figure 1. The existing literature underscores the effectiveness of ACO as one of the foremost meta-heuristic models. ACO draws inspiration from the way real ants modify their behavior and navigate to discover the most efficient routes to their resource destinations. The selection of communication channels is contingent upon the presence of highly concentrated pheromone levels and heuristic values. Our framework is fashioned with inspiration from the adaptation and cooperative strategies exhibited by ants. The iterative process underpins the solution generation. During each iteration, ants derive insights from pheromone trails to formulate solutions. The connections play a pivotal role in estimating the pheromone values used for problem-solving. Ants employ a transition rule to visit nodes in a random manner. Continuous learning facilitates the real-time update of pheromone information, and the evaporation rate of pheromones influences the quality of ants' chosen paths. Our approach takes inspiration from evolutionary algorithms to elevate the quality of ant-generated solutions, ultimately yielding the shortest and most optimal paths.

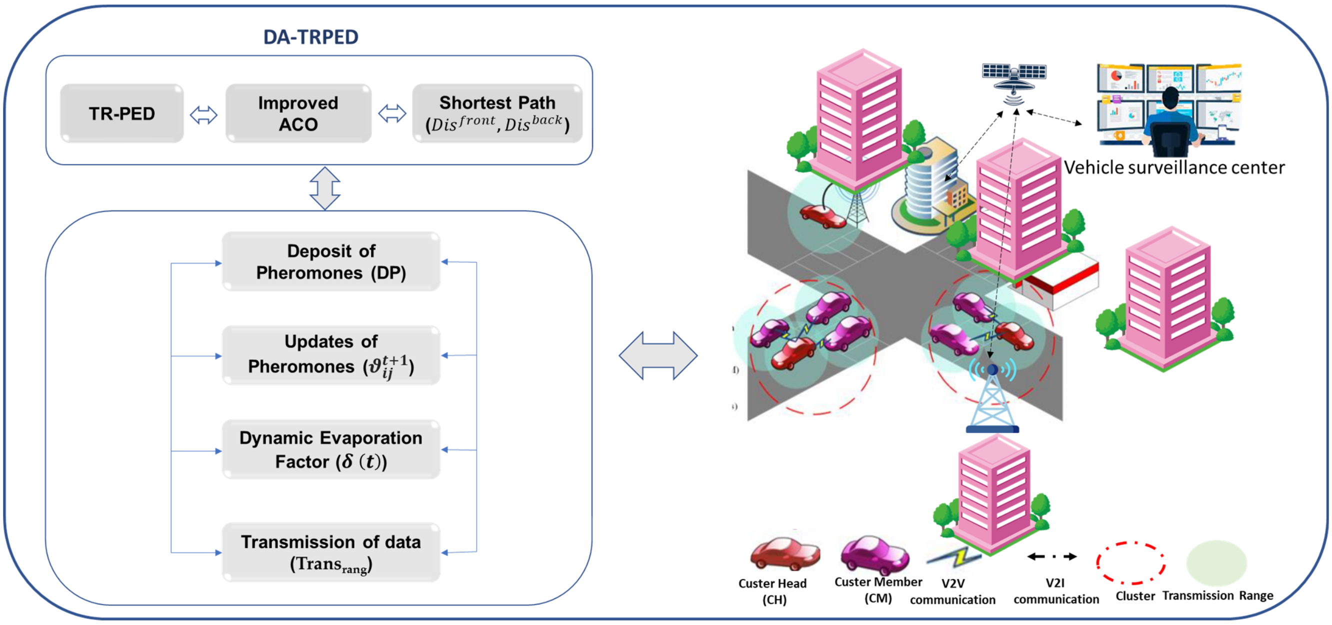

Figure 1. Architecture of the proposed vehicular ad hoc networks (VANETs).

Let us assume that the vehicular networks are fully connected to the environment. In alignment with the 5G networks, the usage of 5G infrastructure covers the highest communication ranges and coverages. GPS helps to localize the position of vehicles. The continuous changes in topology and mobility look for the standardized conditions achieved from the quantity of cluster formation. Better communication is ensured in the minimum count of clusters. Here, ACO is modified for better CH selections for the V2I model. Each vehicular node is treated as point of solution, and the swarm indicates the set of solutions. At a particular period, an ant portrays the IDs of CHs to the routes. This work intends to establish optimal solutions for VANET clustering, achieved by intelligent node selection and energetic evaporation rate. Every vehicle is equipped with 5G and 802.11p. Based on the formed cluster and the V^{Neigh}, the vehicular networks are organized. The integrity of the proposed framework is achieved in two ways: search space modeling and initialization and the CH selection strategy (Algorithm 1).

Algorithm 1: Cluster Head (CH) Selection

Input: No. of ant nodes A
Output: Fittest CHs
For i in set of nodes estimated using (TR-PED)
    Find the node with the highest PEDs
    Set it as the representative node
End for
    Selecting the first node with the best TR-PED values
For ant evolution ( )
    Calculating the distance ratio of each candidate
    The node that fulfills the DP constraints becomes the real clusters
    The representative nodes shares the information and ready for next rounds
End for
  Process Update ()
    If ant_position $\neq$ target then
      Moveto (ant_position + target)
    Leaves pheromones (environment)
  End if
    UpdateType (environment, source area, food sources)
    Nextmove (environment, source area, food sources)
  End Process

3.1. Modeling the Search Space

Our proposed framework represents a substantial advancement in cluster formation, as illustrated in Figure 2. For reference, Table A1 provides an overview of the notations employed in our proposed framework. The search space design is the greatest issue in swarm-based routing. The ants estimate the candidate solution by performing a search in graphical form. Initializing the route is the first step to discovering the optimal routes. The distance oriented approach (DOA) calculates the distance between the current node and its neighbors by forwarding beacon messages. A novel distance metric is introduced to accurately calculate the distances between deployed vehicles named parallel Euclidean distance (PED). PED is symmetric, positive definite, and fulfills points placed in triangle inequalities. It falls between 0 to 1. Let us assume two lanes, a = [a_1, a_2...a_n] and b = [b_1, b_2...b_n] and p = [p_1, p_2...p_n], are the three finite points under Euclidean space P_n, wherein $p \neq a$ and $p \neq b$. The PED is estimated as follows:

$$\mathrm{PED}(a, b; P) = \frac{||a - b||}{||a - p|| + ||b - p||} \tag{1}$$

where

$$||a - b|| = ||a - b||^2 = \sqrt{|a_1 - b_1|^2 + \ldots + |a_n - b_n|^2}$$

The estimated PED is preserved at the routing table. The role of PED estimation is to allocate costs for the node's edge. Initially, the track, distance, node count, and velocity for each ant/vehicle are predefined. For instance, an immediate PED estimates if any vehicle alters its speed. The assigned costs are taken up as the objective function. Because of the VANET's dynamic nature, the path's cost also changes. The purpose of the PED is to eliminate the overheads in cluster and communication. The routes are formed in mesh topology among ants using dynamic aware transmission range on the estimated PED (DA-TRPED) algorithm. The proposed DA-TRPED treats the highway vehicles as a swarm and assigns Trans_{rang} using the estimated local PED of each node. The topology is a directed graph that holds vertices and edges, which is expressed as:

$$\text{Network} = (\text{Vertices V and Edges E}) \tag{2}$$

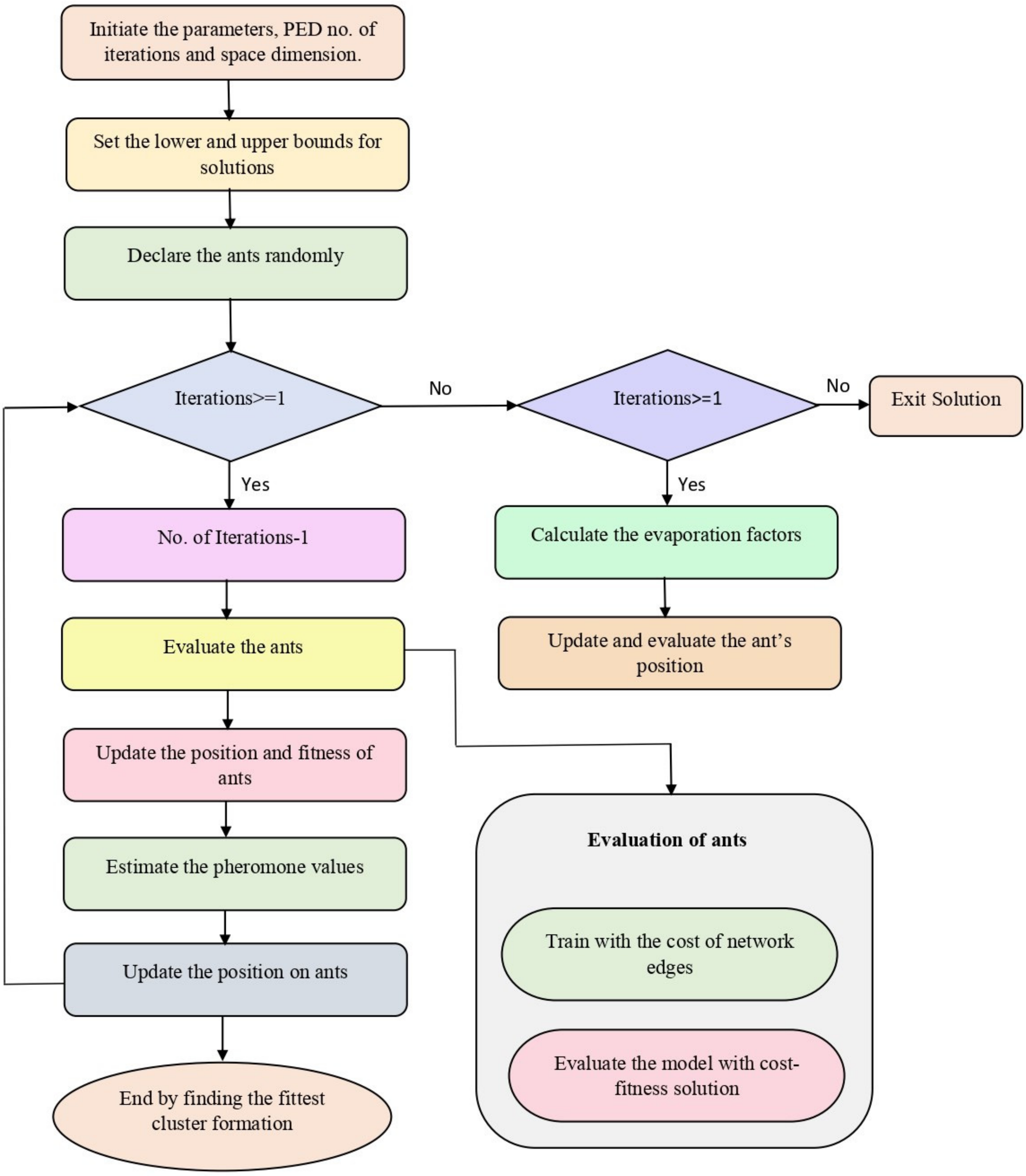

Figure 2. Proposed framework of the DA-TRPED technique in ant colony optimization.

The density of the neighboring vehicles is measured as follows:

$$T^{Density} = \frac{V^{Neigh}}{Dis^{front}} + Dis^{back} \cdot CL * 100 \quad (3)$$

where

$T^{Density}$ denotes the traffic density of the vehicles;
V^{Neigh} denotes count of neighboring vehicles detected;
Dis^{front} denotes the distance between vehicles and the neighbors in front;
Dis^{back} denotes the distance between vehicles and the neighbors behind;

CL denotes the count of lanes in roads.

The density of the local vehicles [40] is measured as follows:

$$L^{Density} = [\frac{\left(1 - T^{Density}\right)}{\rho'} + 1]^{-1} \tag{4}$$

where $L^{Density}$ denotes local density. During the free-flow scenario, the transmission range of the vehicles is measured from

$$Trans_{rang} = TR^{max} \tag{5}$$

Likewise, the transmission range in the normal scenario is measured as follows:

$$Trans_{rang} = TR^{max} * \left(1 - L^{Density}\right) \tag{6}$$

The transmission range in the congested scenario is measured as follows:

$$T^{Density} = \sqrt{\frac{TR^{max} \cdot \ln TR^{max}}{L^{Density}}} + \gamma \cdot TR^{max} \tag{7}$$

Lats, the lowest value of pheromones and the costs are allocated to the edges of the node's network, which is expressed as:

$$\vartheta_{ij}^{t+1}(iter = 1) = \frac{1}{|Nsum|} \tag{8}$$

where *iter* denotes iteration. All vehicular nodes estimate the PED. Thus, a dual performance is given by the vehicles, i.e., it acts as a beacon during the transmission process and estimates the distance to neighboring vehicles. The task is performed uniformly on all vehicles. After the successful completion of PED estimation, the proposed ACO is employed to deposit pheromone relying on the costs function. The ants traverse to find the intenders by using the vehicles' cost and routing table information. The cost of the edges determines the clusters.

3.2. Cluster Head (CH) Selection

Once the clusters are formed, the cluster head is elected by the proposed ACO for transmission purposes.

3.2.1. First-Node Election

Prior methods have randomly selected the first node to select the CHs. Here, a novel way of selecting the first node is carried out to strongly impact the quality of traversing ants with the awareness of pheromones and heuristic values. An additional column is inserted into the pheromone matrix for the first node election. The matrix is updated eventually to find the first node for the better ant tour.

3.2.2. Evolution Rule

The addition of new ants is estimated from the equation below. The objective function for each ant is estimated to conduct a tour. The high heuristic and pheromone values explore the probability of each vertex. The first rule is the addition of a new vertex to the current tour which ensures that only the CMs belong to one cluster. Secondly, two similar transmission ranges of vertices are ignored. It is designed to ensure one CH for a cluster. The process continues until all ants are visited.

$$P_{i,j} = \frac{\vartheta_{ij} \cdot \ Heur_{ij}}{\sum_{k \in N} \vartheta_{ij} \cdot Heur_{ij}} \tag{9}$$

In this context, "i" represents the label of the last vertex added to the current ant's tour, "j" is the label of the next candidate vertex that the ant can choose, "$P_{i,j}$" denotes the selection probability of the edge between vertex i and j. "N" refers to the set of all available vertices for selection while considering the given constraints. Additionally, "ϑ_{ij}" and "$Heur_{ij}$" represent the pheromone and heuristic values associated with the edge between vertex i and j, respectively.

3.2.3. Evaluating the Objective Function

The clustering process is viewed as a multi-objective model to evaluate the objective function. The heuristic value and objective function are expressed as:

$$f_t = Weigh_1.\ f_1\ + Weigh_2.\ f_2 \tag{10}$$

where

$$f_1(\Delta devia) = \sum_{i=1}^{N} Abs\ (\ D - |CM_i\,|\Big) \tag{11}$$

$$f_2\ (Dis - Sum) = \sum_{i=1}^{|\mathrm{N}|} (\sum_{j=1}^{|CM_i|} PED\big(CH_i,\ CM_{i,j}\big)\ ) \tag{12}$$

In this context, "$weigh_1$" and "$weigh_2$" represent weight factors, both of which are set to 0.5. "f_1" corresponds to Δdevia, which is the difference in cluster route length within N. "f_2" is defined as the sum of the distances between CMs (cluster members) and CHs (cluster heads) for all clusters. "D" is a constant value that quantifies the density degree for each cluster. First, the *PED* is computed for all "i" clusters, and it is the sum of the distances between inter-vehicular node $CM_{i,j}$ and CH_i for each cluster "j" within the total cluster set "N".

3.2.4. Estimating Dynamic Evaporation Factor (DEF) under Dynamic Constraints

The conventional ACO uses a static evaporation rate, i.e., 0.05, which lowers the convergence rate and searchability. The inefficiency in the search process lowers the pheromone value and the unvisited vertex. Therefore, tuning evaporating and pheromone values are the metrics used to release the pheromones. Here, the evaporation factor at dynamic constraints (*DP*) is measured as:

$$\delta\ (t) = \vartheta_{ij} * (1 - DP \cdot \delta_{init})) \tag{13}$$

The role of *DP* calculation is to update the pheromone with the best decision for predicting the next ants. Initially, it ranges from [0, 1], which is changed with respect to time. At the range 0, the ants explore the network; as time passes, it moves to 1. In this part, the pheromone change is multiplied by the evaporation factor to justify the convergence speed of the proposed ACO. Finally, the *DP* is estimated as:

$$DP = \{\min\left(1,\ \frac{DP - CS * t}{T}\right) \qquad if,\ DP - CS > 2\ \}$$

$$DP = \{\frac{t}{T} \qquad if,\ DP - CS\ \leq 2\ \} \tag{14}$$

Along with the converging speed foundation, the best solution for ants is also evaluated. The DP-CS to modify the pheromone's speed is defined as [1 − Max_Iteration $_{\text{ants}}$]. Consequently, increasing the ranges might bring the best solutions for ants.

3.2.5. Updating the Pheromones

The quality of ants visiting the network is adjourned by using pheromone values. Finally, the edges are updated with the pheromone values measured as:

$$\vartheta_{ik}\ (t+1) = (1-\vartheta)\delta_{ik}(t) + (1 - \frac{\vartheta_{ik}\ (t)}{(1+f_n)}) \tag{15}$$

3.2.6. Finding the Best Solution

Finally, the fittest CHs are selected as $\text{FittestAnt}_{\text{cost}}$. The proposed ACO stops at the given terminating criteria.

4. Results and Discussion

This section introduces the experimental configuration, parameters, and analysis of the proposed approach. We implemented our method on Network Simulator (NS-2), a versatile simulation tool known for its ability to model various network scenarios and interfaces [41]. The NS2 Simulation parameters utilized in this study are listed in Table 2. The messages or data packets contain both header and payload information, facilitating the monitoring, tracking, and updating of the transmission process. The sample simulation outputs of cluster formation of the proposed DA-TRPED model using the Network Simulator 2 (NS-2) tool are given in Figure 3. The proposed framework was evaluated by five performance parameters, namely, the lifetime of the CHs and CMs, throughput, packet delivery ratio, count of clusters, end-to-end delay, and packet drop rate.

Table 2. Simulation parameters and configurations utilized in NS-2 to evaluate the performance of the proposed VANET model.

Simulation Parameters	Ranges Used
Mobility type	Freeway mobility
Propagation type	2-way ground
Antenna type	Omni-directional
MAC layer protocols	IEEE 802.11p
Beam-forming technology	mmWave
Maximum count of packets in queue	50
Population size (ants)	100
Movement of nodes	Bidirectional
Count of iterations	100
Size of grid	4 km^2
Velocity	22–30 m/s
Count of network nodes	20, 40, 60,80 and 100 vehicles
Protocols	UDP (transport layer)
Traffic type	CBR
Transmission range	Dynamic
Magnitude of packets	512 bytes
No. of executions	20
Confidence rate	90%

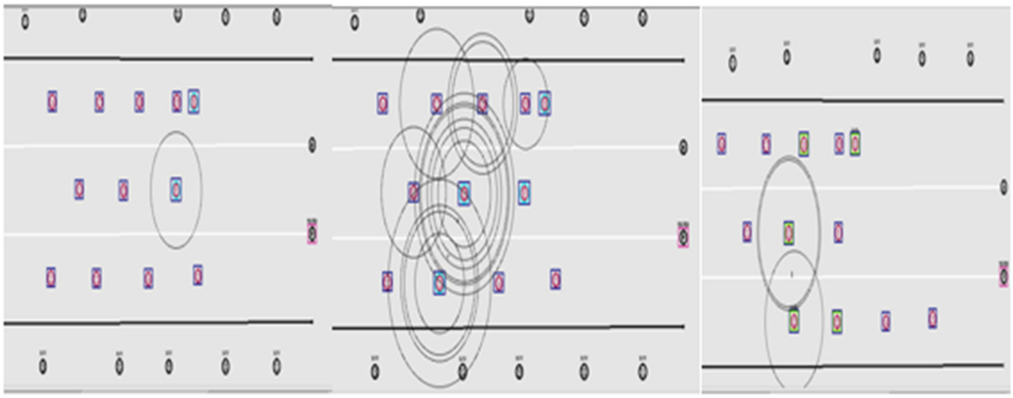

Figure 3. Examples of simulation results showcasing diverse cluster formations using the innovative DA-TRPED model within the NS-2 simulation tool. Circles represents the shape of cluster.

4.1. Throughput Analysis

This metric represents the average number of packets transmitted through the 802.11P communication modules. Table 3 and Figure 4a illustrate the throughput analysis of the DA-TRPED technique, showing that it outperforms other methods. In contrast, the conventional ACO exhibits fluctuations in throughput rates as the vehicle count increases. Interestingly, the proposed technique also shows a reduction in throughput as the number of vehicles increases from 40 to 80. This can be attributed to the estimation of DPEs, which facilitates the communication process and its efficiency.

Table 3. Comparative results of throughput analysis for network performance evaluation.

No. of Vehicles	Distance (m)	DA-TRPED	Conventional ACO
20	0.5	27.23	18.12
40	1.0	28.32	16.87
60	1.5	28.45	14.23
80	2.0	26.53	14.89
100	2.5	27.23	15.24

4.2. Packet Delivery Ratio (PDR) Analysis

The packet delivery ratio (PDR) represents the rate of successfully delivered packets regardless of the vehicles involved. It is a crucial metric that characterizes the performance of the routing network, influenced by factors such as packet volume, transmission range, and network topology. Table 4 and Figure 4b illustrate the results of the PDR analysis. The results indicate that the proposed technique successfully transmitted a greater number of packets, regardless of their volume. The introduction of PED estimation had a significant impact on the cluster formation process, contributing to this improved performance.

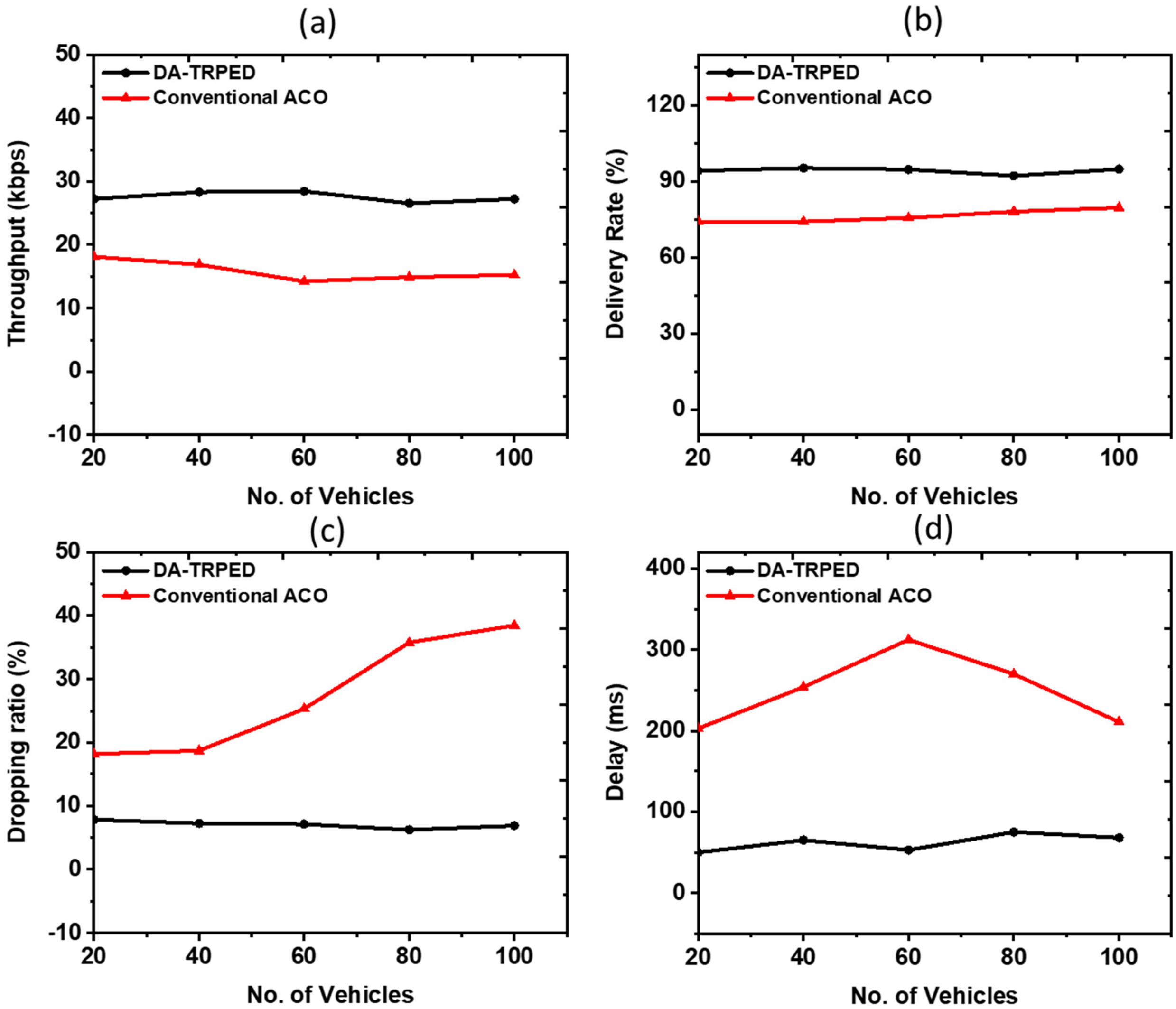

Figure 4. Comparative analysis of the existing ACO and proposed DA-TRPED models. (**a**) Throughput results analysis; (**b**) packet delivery ratio analysis; (**c**) packet dropping ratio analysis; (**d**) end-to-end analysis.

Table 4. Comparative results of packet delivery ratio (PDR) analysis for network performance evaluation.

No. of Vehicles	Distance (m)	DA-TRPED	Conventional ACO
20	0.5	94.21	74.21
40	1.0	95.27	74.12
60	1.5	94.71	75.65
80	2.0	92.21	78.12
100	2.5	94.85	79.63

4.3. Packet Drop Ratio Analysis

The packet drop ratio quantifies the rate of unsuccessful packet transfers within the network. In comparison to the previous ACO method, the proposed technique achieved a significantly lower packet drop ratio, as depicted in Table 5 and Figure 4c. Notably, a substantial contrast is observed in the packet drop analysis. The increased distance between vehicles' placements can impact the packet transmission process. By using PED estimation to position vehicles closer to reduce travel time, the proposed technique substantially decreased the drop ratio. Specifically, the drop ratio of the proposed technique is seven times lower than that of AODV and two times lower than that of ACO.

Table 5. Comparative results of dropping ratio analysis for network performance evaluation.

No. of Vehicles	Distance (m)	DA-TRPED	Conventional ACO
20	0.5	7.82	18.23
40	1.0	7.23	18.74
60	1.5	7.12	25.34
80	2.0	6.23	35.78
100	2.5	6.88	38.47

4.4. End-to-End Delay Analysis

End-to-end delay analysis measures the time taken for packets to traverse the network and is based on calculating the mean delivery time for successfully transmitted packets. This analysis accounts for scenarios where packet transmission, network topology, and network latency exhibit their worst performance. The proposed technique demonstrated superior results compared to other methods, as illustrated in Table 6 and Figure 4d.

Table 6. Comparative results of end-to-end delay analysis for network performance evaluation.

No. of Vehicles	Distance (m)	DA-TRPED	Conventional ACO
20	0.5	50.12	203.1
40	1.0	65.14	254.12
60	1.5	53.12	312.44
80	2.0	75.12	270.14
100	2.5	68.12	211.11

4.5. Cluster Head Lifetime (CHL) Analysis

In our study, we analyzed cluster head (CH) epochs using the TR-PED technique, enabling us to investigate how rapid changes in vehicle positions influence the topology of the vehicular system. These positional changes have the potential to impact the lifetimes of both cluster heads (CHs) and cluster members (CMs). As observed in Table 7 and Figure 5a, when the network has a wider coverage area, it extends the CHs' lifetimes, thus ensuring continuous network connectivity for the CMs. Furthermore, this prolonged CH lifetime results in a decreased frequency of vehicle entries and exits.

Table 7. Comparative results of cluster head lifetime (CHL) analysis for network performance evaluation.

No. of Vehicles	DA-TRPED	Conventional ACO
20	120	185
40	147	180
60	125	177
80	155	173
100	151	156

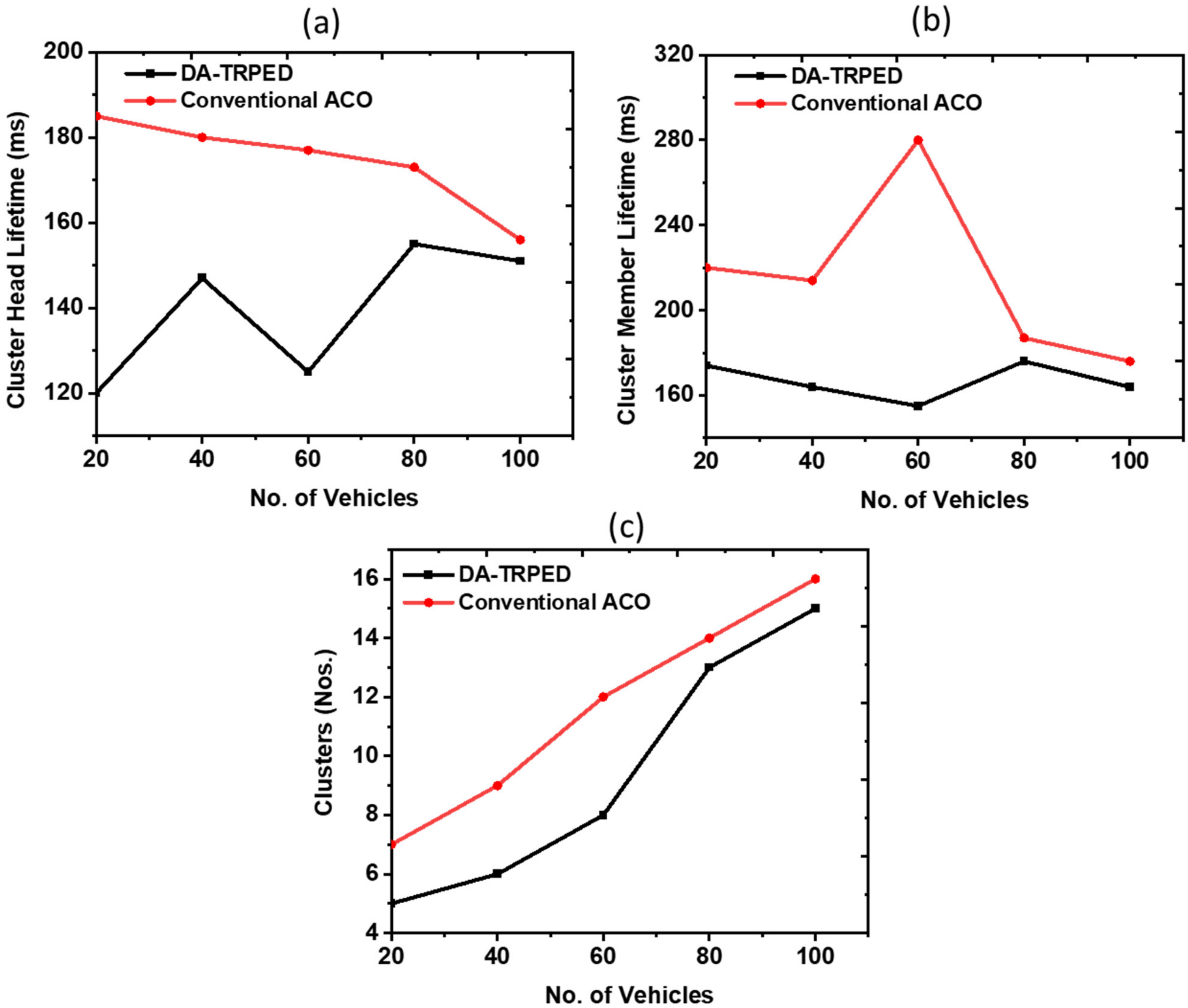

Figure 5. Comparative analysis of the existing ACO and proposed DA-TRPED models. (**a**) Cluster head lifetime (CHL) analysis; (**b**) cluster member lifetime (CML) analysis; (**c**) cluster formation analysis.

4.6. Cluster Member Lifetime (CML) Analysis

Table 8 and Figure 5b clearly illustrate that an increase in cluster head lifetime (CHL) results in corresponding enhancements in cluster member lifetime (CML), thereby ensuring uninterrupted network connectivity.

Table 8. Comparative results of CML analysis for network performance evaluation.

No. of Vehicles	DA-TRPED	Conventional ACO
20	174	220
40	164	214
60	155	280
80	176	187
100	164	176

4.7. Count of Cluster Formation Analysis

The number of clusters plays a crucial role in shaping the functionality of VANETs. The results, shown in Table 9 and Figure 5c suggest that maintaining fair-flow connectivity within the network supports both cluster heads (CHs) and cluster members (CMs) while simultaneously reducing the overall cluster count.

Table 9. Comparative results of cluster formation analysis for network performance evaluation.

No. of Vehicles	DA-TRPED	Conventional ACO
20	5	7
40	6	9
60	8	12
80	13	14
100	15	16

In a recent study, ECBLTR, an enhanced cluster-based lifetime VANET protocol was investigated to evaluate the impact of network sizes and routing protocols on packet delivery ratio and packet loss, average end-to-end delay, and overhead transmission [42]. ECBLTR showed an efficient selection method of CHs through the fuzzy system and an increase in network lifetime compared with CBLTR. Our proposed DA-TRPED technique outperforms the traditional ACO method in terms of packet delivery ratio, dropout rate, latency, and cluster formation.

A small opposite trend is observed when the count of vehicles becomes 60. This is due to the estimation of the dynamic parameter, which brings little network changes. This innovative approach effectively addresses severe congestion problems by optimizing route selection and cluster head assignment during peak hours. Additionally, it leads to a gradual reduction in aggregate distances traveled by vehicles under specific circumstances. However, some limitations are defined in the usage of network cycling and to prevent the search from falling into a local optimum point and global searching potentials.

5. Conclusions

Designing effective routing protocols and network management for VANETs is a challenging task due to the dynamic nature of mobility and data delivery. This challenge highlights the importance of developing dynamic parameters for routing protocols and clustering. While ACO has been used in various ways to optimize solutions, it has often failed to adequately address dynamic constraints. This study introduces a heuristic-based clustering algorithm integrated with an improved ant colony optimizer, resulting in a model that establishes a scalable and stable topology for VANET systems. The proposed model begins by employing a novel approach to select an intelligent initial node and optimizing the search space. Additionally, it enhances the convergence speed of the traditional ACO by adjusting the evaporation factor. The TR-PED algorithm, introduced in this study, accurately estimates the distances between deployed vehicles, ensuring robust VANET connectivity. A comprehensive comparison with the conventional ACO highlights the potential of the proposed approach. The results demonstrate improved simulated performance in terms of packet delivery, packet dropout, delay, and throughput. These innovative design concepts effectively address the challenge of local search space limitations and ultimately achieve reliable, scalable, and efficient vehicle-to-vehicle (V2V) communication. As a future work, the proposed technique can be extended to the concept of cellular automata which helps to select the optimal route by detecting malicious activities.

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Appendix A

Table A1. Notations and their representations utilized in this study.

Notations	Representations
N	Nodes
N_{sum}	Sum of nodes presented in the network
$Trans_{rang}$	Defined transmission range
ΔT_{mod}	Degrees of modification
K	Maximum count of iterations
k	Current iteration
f_1	Deviation assessment of clusters in t
f_2	Summation of distance between CMs and CHs
f_t	Eminency of ant tour
$Weigh_1$, $weigh_2$	Weights allocated between f_1 and f_2, i.e., 0.5
Abs	Absolute value
ED	Euclidean distance
$\lvert CM^i \rvert$	Sum of CMs in cluster
$\lvert k \rvert$	Interval of the clusters
$\vartheta_{ij}^{(t+1)}$	Pheromone trail value in iteration k
δ	Evaporation rate of pheromone
Heur	Heuristic value
TR^{max}	Maximum range of transmission
ρ'	Road facility level, 0.1
γ	Traffic variable; it is constant, 0.25
$T^{Density}$	Density level of traffic
$T^{threshold}$	Threshold level of traffic scenario
$L^{Density}$	Density of resident vehicle
V^{Neigh}	Count of sensed neighbor's vehicle
Dis^{front}	Distance between vehicles and vehicles in front
Dis^{back}	Distance between vehicles and vehicles behind
CL	Count of lanes in roads

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