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Decisiveness PSO-Based Gaussian AOMDV (DPSO-GAOMDV) Routing Protocol: Smart Routing for Dynamic Traffic Conditions in Stochastic Vehicular Ad Hoc Network

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Abstract – Vehicular Ad Hoc Networks (VANETs) have gained prominence in vehicular communication due to their potential to enhance road safety, traffic efficiency, and infotainment services. However, the evolution of Stochastic VANETs (SVANETs) has introduced a layer of uncertainty, where vehicular interactions are influenced by dynamic factors such as varying traffic conditions, changing communication environments, and unpredictable link qualities. Routing within SVANETs presents distinct challenges stemming from the stochastic nature of the environment. Traditional routing protocols struggle to maintain reliable connections amidst fluctuating link conditions, leading to increased latency, dropped packets, and inefficient route utilization. The novel "Decisiveness PSO-Based Gaussian AOMDV (DPSO-GAOMDV) Routing Protocol" is introduced to address these challenges. This innovative protocol combines the predictive power of Gaussian-Anticipatory On-Demand Distance Vector (GAOMDV) routing with the dynamic adaptability of Particle Swarm Optimization (PSO). GAOMDV's ability to anticipate link stability using Gaussian distribution is integrated with DPSO's agility in optimizing routing decisions. The simulation phase of the study evaluates the DPSO-GAOMDV protocol under various stochastic vehicular scenarios. The protocol's performance is thoroughly analyzed by emulating real-world traffic conditions and communication dynamics. The simulation results underscore the protocol's efficacy in reducing route maintenance overhead, improved packet delivery ratios, and enhanced network stability. The predictive insights and dynamic optimization mechanisms showcase its potential to drive innovative, resilient and efficient routing strategies in the face of stochastic vehicular conditions.

Index Terms – Ad Hoc Network, Bio-Inspired Optimization, Routing, Stochastic, VANET, Vehicle.

1. INTRODUCTION

Ad Hoc networks introduce a new dimension to connectivity, operating beyond the bounds of conventional setups. These networks establish real-time connections, enabling devices to communicate without rigid infrastructure. Ad Hoc networks exemplify adaptability and swift data exchange from emergency response scenarios to spontaneous gatherings.

1.1. VANET

Vehicular Ad Hoc Networks (VANETs) stand at the forefront of modern communication technologies, presenting a paradigm shift in transportation systems. These networks establish a novel means for vehicles to communicate seamlessly with each other and with roadside infrastructure, amplifying road safety, traffic management, and overall driving experiences[1]. Tailored as a specialized subset of Mobile Ad Hoc Networks (MANETs), VANETs are uniquely designed to address the dynamic challenges intrinsic to the vehicular environment.

Within VANETs, vehicles are outfitted with wireless communication devices such as Wi-Fi or Dedicated Short-Range Communication (DSRC) tools, cultivating an interwoven network on the road[2]. This interconnectedness spawns many applications to heighten road safety and traffic efficiency. Paramount among these is the real-time distribution of vital safety information - encompassing alerts about accidents, road impediments, and abrupt shifts in traffic conditions. Drivers can make enlightened choices by

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disseminating these alerts to nearby vehicles, mitigating collision risks and averting traffic bottlenecks[3].

VANETs facilitate the actualization of intelligent traffic management systems. Through communication between vehicles and traffic infrastructure, such as traffic signals, traffic flow optimization, congestion reduction, and fuel efficiency augmentation are possible[4]. This bi-directional exchange underpins the implementation of adaptive traffic signal timing, where signals autonomously adapt based on prevailing traffic dynamics, culminating in fluid traffic patterns and minimized travel durations[5].

1.2. SVANET

Stochastic Vehicular Ad Hoc Networks (SVANETs) represent an innovative evolution of traditional VANETs, introducing a probabilistic dimension to how vehicles communicate and interact on the road. In SVANETs, the focus shifts from deterministic models to embracing uncertainty and randomness inherent in real-world vehicular environments[6].SVANETs leverage stochastic processes to capture the unpredictable nature of vehicular behaviors, traffic patterns, and environmental conditions. Unlike conventional VANETs, where communication and decision-making are often based on fixed rules or predictions, SVANETs incorporate variability and randomness, making them better suited to handling traffic scenarios' complex and ever-changing nature[7].

These networks enable vehicles to make decisions based on probabilities and statistical information. This approach can lead to more adaptive and context-aware actions. For instance, a vehicle could calculate the probability of encountering congestion on different routes and choose the one with the lowest expected delay. Likewise, SVANETs can facilitate cooperative maneuvers, such as merging, where vehicles assess the likelihood of other vehicles' responses before executing a lane change[8].SVANETs have applications in predicting traffic flow and congestion. By analyzing historical data and employing stochastic modeling techniques, these networks can generate probabilistic forecasts for traffic conditions, aiding in proactive traffic management strategies. This predictive capability can lead to optimized traffic flow and reduced congestion, benefiting individual drivers and overall transportation efficiency[9], [10].

Table 1 VANET and SVANET Difference

Aspect	VANET	SVANET
Communication	Follows predefined protocols	Incorporates stochastic processes
Decision-Making	Rule-based decisions	Probabilistic decision-making
Traffic Prediction	Deterministic models	Uses stochastic modeling for predictions
Adaptability	Less adaptable to variability	Adapts to uncertain and random conditions
Realism	Reflects fixed scenarios	Models real-world variability and randomness
Traffic Management	Standard strategies	Optimizes based on probabilistic information
Research Focus	Communication efficiency	Stochastic modeling and adaptive algorithms
Challenges	Handling topology changes	Dealing with uncertainty and conflicting data

1.3. Difference between VANET and SVANET

VANET and SVANET are networks designed to improve vehicular communication and enhance transportation systems. While they share similarities in their objectives, SVANET introduces a significant twist by incorporating stochastic elements to better adapt to the unpredictable nature of real-world traffic environments[11], [12]. Table 1 provides the difference between VANET and SVANET.

1.4. Routing in SVANET

Routing in SVANETs represents a critical aspect of managing vehicle communication in dynamic and uncertain traffic environments. Unlike traditional vehicular networks, SVANETs integrate stochastic elements to accommodate the unpredictable nature of vehicular movements, traffic patterns, and communication conditions[13]. This introduces challenges and opportunities that require innovative routing approaches to ensure efficient data exchange and reliable connectivity[14]–[16]. In SVANETs, the primary goal of routing remains the same: to determine the optimal paths for data transmission between source and destination vehicles. The vehicular behavior's dynamic and stochastic nature demands routing strategies that can adapt in real-time to varying conditions, such as changes in traffic density, road conditions, and communication quality. Due to the inherent uncertainty, traditional routing protocols designed for stable networks might not perform optimally in SVANETs[17].

1.4.1. Challenges in Routing in SVANET

Routing in SVANETs presents notable challenges due to the dynamic and uncertain nature of vehicular environments:

- Uncertain Communication: Fluctuating signal strengths and mobility affect communication quality, necessitating robust routing strategies.
- Probabilistic Metrics: Selecting appropriate probabilistic metrics that capture both stochastic elements and network requirements is vital.
- Cooperative Decisions: Enabling cooperative routing while addressing trust, privacy, and data reliability issues is crucial.
- Resource Constraints: Creating routing algorithms that conserve vehicle resources while maintaining performance is a concern.
- Real-Time Adaptation: Quick adaptation to changing conditions while minimizing disruptions is necessary.

1.5. Problem Statement

In SVANETs, efficiently navigating through varying traffic conditions and congestion is a substantial challenge. The unpredictable nature of vehicular movements and changing road conditions can lead to suboptimal route choices and increased travel times. Developing routing strategies that intelligently incorporate real-time traffic information and probabilistic modeling is essential to address this issue.

The problem involves designing routing protocols that dynamically adapt to emerging traffic patterns, utilizing historical data and predictive models to make informed decisions. Integrating traffic and congestion awareness into SVANET routing can significantly improve overall network efficiency, reduce congestion-related delays, and enhance the driving experience.

1.6. Motivation

The motivation to address traffic awareness and congestion challenges in SVANETs arises from the pressing need to enhance traffic flow efficiency and reduce congestion-related delays. As urban roads become increasingly congested and traffic patterns unpredictable, traditional routing approaches often fail to optimize routes for real-time conditions. By devising routing strategies incorporating real-time traffic data and probabilistic models, we can unlock the potential to significantly improve vehicular navigation and overall network performance. The motivation stems from the vision of transforming SVANETs into more competent and responsive transportation systems, where vehicles intelligently adapt to traffic fluctuations, thereby minimizing travel times and contributing to more sustainable urban mobility.

1.7. Objective

The primary objective of this research is to develop novel routing mechanisms that enhance traffic awareness and congestion management within Stochastic Vehicular Ad Hoc Networks (SVANETs). This objective seeks to bridge the gap between traditional routing approaches and the dynamic nature of vehicular environments. By leveraging real-time traffic data and probabilistic modeling, we aim to design routing protocols that intelligently adapt to changing traffic patterns, optimizing efficient routes and minimizing congestion-related delays. The overarching goal is to create a responsive and adaptable SVANET infrastructure that empowers vehicles to make informed routing decisions, contributing to smoother traffic flow, reduced travel times, and improved overall road safety.

1.8. Organization of the Paper

In Section 1, the introduction provides an overview of the research, beginning with a description of VANET and SVANET. The section then delves into the differences between these two networks types and explores the challenges associated with routing in SVANET. Section 2 presents a comprehensive literature review, offering an in-depth analysis of prior research in the field. Section 3 introduces the Decisiveness PSO-Based Gaussian AOMDV (DPSO-GAOMDV) Routing Protocol. This section highlights their differences, this covers key components such as Gaussian AOMDV, Particle Swarm Optimization (PSO), and Decisiveness Particle Swarm Optimization (DPSO). Additionally, it discusses the fusion of DPSO and GAOMDV to present a unified routing protocol. Section 4 details the simulation settings, providing information on the environment and metrics used in the evaluation process. Section 5 presents the results of the simulations and engages in a comprehensive discussion of DPSO-GAOMDV's performance compared to other protocols. Finally, Section 6 provides a concise

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conclusion summarizing the key findings, emphasizing the significance of DPSO-GAOMDV in SVANET routing and suggesting potential avenues for future research and protocol improvement.

2. LITERATURE REVIEW

"Trust-Based Geographic Routing (TRGV)" [18] is introduced as an advanced routing protocol designed for VANETs. This protocol leverages trust as a critical factor in route selection decisions. TGRV optimizes geographic routing paths by considering the trustworthiness of neighboring vehicles, ensuring reliable and secure data transmission. This approach enhances communication efficiency while mitigating the risks of malicious or compromised nodes. "Cauchy Density-Based Clustering (CDAC)" [19] is proposed as a clustering algorithm designed for VANETs in 3D road environments. This algorithm, named 3D Cauchy Density-Based Algorithm for Clustering (CDAC), optimizes cluster formation by leveraging the Cauchy density function. By considering the spatial distribution of vehicles in three-dimensional road environments, CDAC forms clusters that accurately represent local vehicle concentrations. "Energy efficient clustering" [20] takes a dual-pronged approach to enhance energy conservation and routing efficiency. The protocol dynamically organizes vehicles into clusters, leveraging heuristic optimization techniques and effectively managing communication and resource allocation. By considering real-time data and vehicular movement patterns, HEC-HO Routing optimizes the formation and maintenance of clusters to minimize energy consumption while ensuring effective communication.

"Particle Swarm Optimized OLSR with Enhanced Routing (PSO-OLSRER)" [21] revolutionizes VANET routing by integrating multi-objective particle swarm optimization into the OLSR protocol. PSO-OLSRER harnesses the power of real-time vehicle data and environmental insights to enhance routing decisions. By leveraging multi-objective optimization, the protocol tailors its parameters to minimize delays and maximize throughput while considering the dynamic nature of vehicular networks. "Adaptive Opportunistic Routing" [22] involves an intricate process of selecting the most suitable paths for message propagation. This process heavily relies on adaptively prioritizing candidate forwarding sets. The routing algorithm optimizes message delivery in dynamic vehicular environments by efficiently managing these sets. The approach leverages real-time information regarding vehicle movements, connectivity, and potential relay nodes to dynamically adjust forwarding priorities. "TS-CAGR: Geocast Routing" [23] introduces a novel geo-cast routing protocol named Traffic Sensitive Connectivity-Aware Geocast Routing (TS-CAGR) designed for the Internet of Vehicles (IoV). This protocol optimizes communication by considering both traffic conditions and connectivity aspects. TS-CAGR intelligently selects and routes messages to vehicles within a specific geographic area, ensuring efficient data dissemination while minimizing network congestion.

"Obstacle Anticipation-Integrated Routing (OAIR)" [24] redefines VANET routing through the pioneering "Obstacle Prediction-Based Routing Protocol (OPBRP)." OAIR revolutionizes conventional routing strategies by seamlessly incorporating predictive obstacle mechanisms. Real-time input from vehicular sensors and environmental cues empowers OAIR to foresee upcoming obstacles such as traffic congestion, accidents, and roadblocks. "InfoWave System" [25] is proposed to efficiently model and analyze a traffic warning message dissemination system in VANETs. This innovative system capitalizes on the dynamic nature of VANETs by employing a decentralized approach, utilizing vehicle-to-vehicle communication to relay crucial traffic warning messages. "IoT-Powered GridEdge Solution" [26] is proposed to seamlessly integrate IoT and edge cloud computing to enable intelligent microgrid energy management in VANETs empowered by machine learning. This innovative approach leverages IoT sensors to gather real-time data from distributed energy resources within the microgrid.

"AuthML-QoS Route Enhancer" [27] is proposed for a novel approach that combines bi-linear mapping and machine learning techniques to develop an authentication routing protocol to elevate the quality of service within VANETs. This innovative protocol employs bi-linear mapping for secure authentication, ensuring the validity of communication nodes. "Fog-ROCL: Optimal VANET Fog Deployment" [28] is proposed for an advanced approach that introduces Fog-ROCL, a system focused on optimal configuration and localization of Fog-based Roadside Units (RSUs) within VANETs. By employing a fog computing paradigm, Fog-ROCL strategically determines the ideal placement and configuration of RSUs to enhance network coverage, reduce latency, and ensure efficient data processing at the network edge. "CloudGuardKeyCheck: Real-time VANET Security" [29] is proposed for an innovative mechanism that introduces CloudGuardKeyCheck, designed to enhance cloud storage and security in VANETs. By integrating real-time cloud monitoring metrics, this system establishes an efficient essential validation process that ensures the integrity of data transmission and storage. "SSDN-Enhanced VANET Handover: Seamless Mobility" [30] is proposed for a sophisticated handover scheme that leverages Software-Defined Vehicular Networking (SSDN) to optimize handovers within VANETs. By integrating the Media Independent Handover (MIH) framework, this system enables efficient transitions between different network access technologies while maintaining seamless connectivity.

"Ant Colony Optimization-based Self-Healing Routing Protocol (ACO-SH)"[31] introduces an innovative approach

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to enhancing the resilience of communication in dynamic networks. By harnessing the power of Ant Colony Optimization (ACO), this protocol ensures reliable data routing even in the face of disruptions. The protocol's self-healing capabilities allow it to detect and circumvent faulty routes, adapting in real-time to network changes. The protocol optimizes route selection, mitigates downtime, and enhances overall network robustness by emulating the behavior of ant colonies that find optimal paths. "Hybrid Genetic Firefly Algorithm-Based Routing Protocol (HGFA)"[32] is an advanced approach aiming to enhance the efficiency of data routing within VANETs. This innovative protocol combines the strengths of Genetic Algorithms (GA) and Firefly Algorithms (FA) to optimize route selection. The protocol adapts to dynamic network conditions and varying vehicular environments by iteratively evaluating and refining potential routes. The Genetic Algorithm phase focuses on selecting promising routes through crossover and mutation, while the Firefly Algorithm phase optimizes the selected routes by mimicking firefly behavior.

2.1. Research Gap

There is a significant research gap in developing routing protocols tailored to these networks' stochastic and dynamic nature. SVANETs introduce unique challenges due to their inherent unpredictability and randomness in vehicular communication patterns. A critical research need lies in creating robust and adaptive routing protocols specifically designed to navigate the stochastic characteristics of SVANETs. These protocols should prioritize reliable data transmission and adaptability to dynamic changes in network conditions, including vehicular mobility patterns, varying densities, intermittent connectivity, and the stochastic behavior of vehicles. Additionally, addressing uncertainty in SVANETs is paramount, necessitating innovative solutions to optimize communication efficiency, enhance security, and efficiently allocate network resources in these unpredictable factors. Furthermore, research should explore novel techniques for optimizing energy consumption and minimizing latency, all while considering the stochastic nature of the network environment. The research gap in SVANETs calls for holistic and adaptive routing solutions to address vehicular communication's inherent stochasticity and dynamism in these networks.

3. DECISIVENESS PSO-BASED GAUSSIAN AOMDV (DPSO-GAOMDV) ROUTING PROTOCOL

3.1. Gaussian AOMDV

Gaussian AOMDV (GAOMDV) is an enhanced version of the Ad Hoc On-Demand Distance Vector (AOMDV) routing protocol, designed to improve the efficiency and adaptability of routing in mobile ad hoc networks. GAOMDV integrates Gaussian principles to optimize route selection based on a combination of performance metrics. The protocol focuses on latency, packet loss, and throughput to quantify route efficiency. Algorithm 1 provides the working of Gaussian AOMDV.

3.1.1. Efficiency Quantification for Routes

Gaussian AOMDV (GAOMDV) is the proposed enhancement of the Ad Hoc On-Demand Distance Vector (AOMDV) routing protocol using Gaussian principles. The initial step involves quantifying the efficiency of each discovered route R_i. This process comprehensively considers key performance metrics such as latency (L_i), packet loss (P_i), and throughput (T_i).Efficiency for each route is computed using Eq.(1).

$$E_i = f(L_i, P_i, T_i) \quad (1)$$

The outcome of Eq.(1) is a quantitative representation of a route's effectiveness, and it is formed by amalgamating the significant performance metrics.

3.1.2. Gaussian-Like Probability Allocation

Central to the enhancement strategy is the innovative notion of allocating probabilities to routes by harnessing a Gaussian-like distribution. This approach utilizes the calculated efficiencies to establish a distribution centred around the average efficiency $\bar{E}$. Subsequently, each route's probability (P_i) is determined through a dedicated function g, contextualizing the route's efficiency concerning the calculated average. The probability allocation process can be mathematically defined as Eq.(2).

$$P_i = g(E_i, \bar{E}) \quad (2)$$

The probability allocation ensures that routes with higher efficiencies receive elevated probabilities, creating a dynamic framework for route selection.

3.1.3. Dynamic Path Selection

Integrating Gaussian principles into the enhancement involves introducing a dynamic path selection mechanism. Upon the necessity to transmit a data packet, the protocol strategically identifies the route R_j with the highest assigned probability (P_j) for data forwarding. This selection process can be represented mathematically as Eq.(3).

$$R_j = \arg max_{R_i} P_i \quad (3)$$

By favoring the path with the highest probability, the protocol effectively prioritizes routes, demonstrating superior efficiencies.

3.1.4. Adaptive Probability Updates

A fundamental aspect of the Gaussian-based enhancement is its responsiveness to real-time network conditions. As data

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packets traverse the network, the protocol continually updates efficiencies and recalculates probabilities based on current observations. This adaptability guarantees that probabilities remain synchronized with the evolving efficiency landscape, expressed in Eq.(4).

$$P_i(t) = g\left(E_i(t), \bar{E}(t)\right) \quad (4)$$

This dynamic adjustment mechanism enhances the protocol's capability to make informed and optimized route selections, aligning with the network's ever-changing dynamics.

3.1.5. Enhanced Network Resilience

The enhanced routing mechanism augments network resilience by imbuing the AOMDV protocol with Gaussian-inspired principles. Routes with sustained historical efficiencies receive heightened probabilities, leading to a distribution of traffic that circumvents potential congestion points and optimizes overall data flow.

3.1.6. Minimized Packet Loss and Latency

The probabilistic path selection strategy in Gaussian-based AOMDV significantly reduces packet loss and latency. Efficient routes are favored, minimizing the chances of data loss and reducing delays in data delivery, which is particularly critical in dynamic ad hoc scenarios.

Input:

- Discovered routes R_i with performance metrics: Latency (L_i), Packet loss (P_i), throughput (T_i)
- Current time t

Output:

- Selected route for data forwarding R_j

Procedure:

Step 1: Efficiency Quantification for Routes

- For each route R_i, calculate efficiency E_i using the given metrics: $E_i = f(L_i, P_i, T_i)$

Step 2: Gaussian-Like Probability Allocation

- Calculate the average efficiency $\bar{E}$ across all routes.

✓ For each route R_i, compute probability P_i using a function g based on E_i and $\bar{E}$:$P_i = g(E_i, \bar{E})$

Step 3: Dynamic Path Selection

- When there's a need to transmit a data packet:

✓ Select the route R_j with the highest assigned probability P_j for data forwarding.

Step 4: Adaptive Probability Updates

- Continuously update route efficiencies based on real-time observations.
- Recalculate probabilities for each route using the updated efficiencies and the current average efficiency.

Step 5: Enhanced Network Resilience

- Favor routes with sustained historical efficiencies by assigning higher probabilities.

Step 6: Minimized Packet Loss and Latency

- Prioritize routes with elevated probabilities to reduce packet loss and latency during data forwarding.

Algorithm 1 Gaussian AOMDV

3.2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) operates as a bio-inspired optimization method, drawing inspiration from the collective behavior of birds foraging for the best food source. A dynamic algorithm can efficiently tackle complex optimization problems across diverse domains. In PSO, a group of "particles" simulates the avian swarm, with each particle representing a potential solution. This abstraction allows the particles to traverse the solution space like birds exploring their environment. The process involves continuous refinement: particles adjust their solutions based on their successes (personal best) and the collective achievements of the swarm (global best). This cooperative exchange of information helps particles effectively navigate the complex landscape of possibilities, dynamically converging toward optimal solutions. PSO's ability to replicate nature's collaborative exploration makes it a versatile tool for solving intricate optimization challenges.

At its core, PSO encapsulates the synergy between individual and group learning. With every iteration, particles adapt their trajectories influenced by their own past experiences and the accomplishments of their companions. This enables the algorithm to progressively fine-tune solutions while exploring new improvement avenues. The balance between exploitation and exploration mirrors the strategies employed by birds seeking sustenance in their habitats. By mimicking this process, PSO has demonstrated its prowess in addressing complex optimization problems in various fields, spanning engineering, economics, machine learning, and beyond. This innate ability to harness the essence of collective intelligence found in nature renders PSO a valuable and effective optimization approach. Algorithm 2 provides a structured and precise representation of the PSO process.

Step 1: Initialization: Commence by initializing a collection of particles, analogous to birds, with random solutions and velocities.

Step 2: Evaluation: Assess the fitness of the solution proposed by each particle within the given problem domain.

Step 3: Personal Best Tracking: Update each particle's best solution based on its appraised fitness. This represents the most favorable solution the particle has discovered thus far.

Step 4: Global Best Tracking: Determine the optimal solution among all particles, termed the global best. This signifies the optimal solution unearthed by any particle in the entire swarm.

Step 5: Velocity Adjustment: Adapt the velocity of each particle contingent on its prevailing velocity, personal best, and global best. This guides particles toward enhanced solutions.

Step 6: Solution Updating: Revise each particle's position (solution) predicated on its present position and the recalibrated velocity.

Step 7: Collaborative Search: Particles communicate indirectly by observing the accomplishments of their counterparts. They modify their trajectories to investigate regions where fellow particles have ascertained superior solutions.

Step 8: Iterative Process: Recur through steps 2 to 7 for a predetermined number of iterations or until a satisfactory solution is achieved.

Step 9: Convergence: As particles iterate, they gradually concentrate on sectors yielding superior outcomes, progressively converging towards the optimal solution.

Algorithm 2 PSO

3.2.1. Issues in PSO

This research has identified the top five issues in PSO, summarized below:

- Premature Convergence: PSO can converge too early to a suboptimal solution, missing the best overall solution.
- Diversity Loss: The swarm might lose diversity, limiting solution space exploration.
- Parameter Sensitivity: PSO's performance heavily depends on parameter tuning, which can be challenging.
- Scalability Concerns: PSO struggles with high-dimensional and complex problems.
- Variable Convergence Speed: Convergence can be fast in some cases but slow in others, influenced by factors like swarm size and parameters.

This research attempts to overcome the issues in PSO by making significant modifications described in Section 3.3.

3.3. Decisiveness Particle Swarm Optimization (DPSO)

DPSO is a meta-heuristic algorithm to obtain the optimal CH of the cluster U_s in the shortest amount of time. Let $E_s = \{m_1^s, m_2^s, m_3^s, \ldots.. m_{D_s}^s\}$ be the searching space of cluster U_s, where $w = 1,2,3, \ldots., D_s$ and m_w^s represent the position of the SN $e_w \omega U_s$. To find the SN $e_w \omega U_s$ with the best position $m_w^s \omega E_s$, which offers the minimal value of the fitness function $G(s, w)$, is the goal.

3.3.1. Particle Representation and Initialization

To find the best optimal solution in a search space of Y dimensions, E, the PSO method is utilized, with a maximum and minimum search radius of R_{Max} and R_{Min} respectively. DPSO refers to each swarm member as a $d_s, s\omega[1,2,3, \ldots, T]$ particle, where $T > 1$ is the swarm size. The particle d_s is entirely defined by its present position in the vector $P_{s,y}^a \omega E$, its current velocity $R_{s,y}^a$, and its best position $M_{s,y}^a \omega E$, where y is the dimension of the vectors, at each iteration $a = 1,2,3, \ldots$ These scalars are represented as Eq.(5) to Eq.(7)

$$P_{s,y}^a = \left(p_{s,1}^a, p_{s,2}^a, \ldots.. p_{s,y}^a\right)^F, \tag{5}$$

$$R_{s,y}^a = \left(r_{s,1}^a, r_{s,2}^a, \ldots.. r_{s,y}^a\right)^F \tag{6}$$

$$M_{s,y}^a = \left(m_{s,1}^a, m_{s,2}^a, \ldots.. m_{s,y}^a\right)^F \tag{7}$$

For instance, if $y = 2$, then $P_{s,2}^a = (p_{s1}^a, p_{s2}^a)$, , and $R_{s,2}^a = (r_{s1}^a, r_{s2}^a)$, and $M_{s,2}^a = (m_{s1}^a, m_{s2}^a)$. The particle d_s moves because the vector changes its position $R_{s,y}^a$, which is a position shift that can be changed. The vector $M_{s,y}^a$ describes the most advantageous personalized position that the particle d_s has ever been in E up to iteration a (i.e., the position corresponding to the best fitness value).

3.3.2. Fitness Function and Best Position Updates

The efficiency of particle d_s at point $P_{s,y}^a$ is measured using a fitness function g that is relevant to the problem to be solved, where $g: B^y \to B$. The function of fitness g takes as a parameter $P_{s,y}^a$ and returns a significant value that can be compared to the value of $g\left(P_{s,y}^{a-1}\right)$. The issue of identifying the significant (i.e., minimal) value with the best fitness value is expressed as Eq.(8).

$$P_{s,y}^a = \begin{cases} P_s^{a-1} g\left(P_{s,y}^a\right) > g\left(P_{s,y}^{a-1}\right) \\ P_{s,y}^a \; g\left(P_{s,y}^a\right) \le g\left(P_{s,y}^{a-1}\right) \end{cases} \tag{8}$$

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Eq.(9) is expressed to identify the maximal best fitness value.

$$P_{s,y}^{a} = \begin{cases} P_{s}^{a-1} g\left(P_{s,y}^{a}\right) < g\left(P_{s,y}^{a-1}\right) \\ P_{s,y}^{a}\ g\left(P_{s,y}^{a}\right) \geq g\left(P_{s,y}^{a-1}\right) \end{cases} \tag{9}$$

3.3.3. Global Best Position Update

The local optimal position, denoted by the vector $S_{s,y}^{a}$, is derived from the particle's d_s implicit information exchange with a subset of the swarm located nearby. The vector $S_{s,y}^{a}$ is referred to as a global best position vector j_y^a, and is given as Eq.(10) if the particle d_s considers all of the people in it as its topological neighbors.

$$j_y^a = \begin{cases} arg\left[max\left(g(M_{1,y}^{a}), g(M_{2,y}^{a}), \ldots.. g(M_{T,y}^{a})\right)\right], maximum\ problem \\ arg\left[min\left(g(M_{1,y}^{a}), g(M_{2,y}^{a}), \ldots.. g(M_{T,y}^{a})\right)\right], minimum\ problem \end{cases} \tag{10}$$

3.3.4. Setup and Maintenance Phases

Two key phases are involved in implementing the PSO algorithm: (i) Setup and (ii) Maintenance. In the setup phase, E is filled with a random distribution of particles. The particle d_s is used to symbolize a potential answer to the given problem. In the maintenance phase, this research utilizes the particle's location to determine the value of $M_{s,y}^{a}$. Based on Eq.(10), the optimal swarm position is defined as the particle's location with the highest fitness value or j_y^a.

The operational stage is carried out in a series of iterations using Eq.(11) and Eq.(12). Each particle's location and velocity d_s are modified during each iteration, that is $a + 1$.

$$P_{s,y}^{a} = P_{s,y}^{a-1} + r_{s,y}^{a} \tag{11}$$

And

$$R_{s,y}^{a} = \varpi R_{s,y}^{a-1} + \delta_1 \varphi_1 \odot \left(M_{s,y}^{a} - P_{s,y}^{a}\right) + \delta_2 \varphi_2 \odot \left(j_y^a - P_{s,y}^{a}\right) \tag{12}$$

Where ϖ is the inertial mass or the constriction coefficient that determines how much the prior velocity affects the present velocity. The value denotes the particle's cognitive weighting factor δ_1, whereas the constant denotes the social weighting factor of a swarm δ_2. In addition, both φ_1 and φ_2 in the range [0,1] have evenly distributed random vectors. Hadamard product comprises two matrices of the same size, denoted by the symbol $\odot$. Thanks to the first phrase in Eq.(12), parties seek a larger region and expand their horizons.

The data of the particle d_s is included in the second term $\left(M_{s,y}^{a} - P_{s,y}^{a}\right)$, and it is referred to as a cognitive term. Since the third term $\left(j_y^a - P_{s,y}^{a}\right)$ depends on input from other particles (i.e., knowledge gained through the collaboration of the particles), it is labeled as a "social term." There is an effect on a particle's velocity from the second and third terms. A maximum iteration count, denoted by Max.

3.3.5. Adjustment Phase

The adjustment phase involves four types of DPSO updates: Particle Velocity Update, Global Best Velocity Update, Present Phase Velocity Update, and Final Velocity Update.

(i). Particle Velocity Update

In this stage, the DPSO initiates by updating the velocities of individual particles within the swarm. Each particle's velocity is adjusted based on its current velocity, the cognitive component (personal best), the social component (global best), and the present phase. The inertia weight used in this stage is recalculated to influence the balance between exploration and exploitation.

This recalculated inertia weight governs the particle's responsiveness to its own experience and the experiences of others. By recalibrating the inertia weight, the algorithm aims to ensure a controlled search space exploration while maintaining a bias towards exploiting promising solutions.

(ii). Global Best Velocity Update

After the initial velocity update, the DPSO progresses to stage two, which focuses on updating the velocities of particles based on the global best solution found within the swarm. Similar to the first stage, the inertia weight is recalculated to adjust the balance between exploration and exploitation, considering the influence of the global best. This stage reinforces the convergence of particles towards the most promising solution found by any particle in the swarm.

(iii). Present Phase Velocity Update

Moving on to stage three, the DPSO refines the particles' velocities based on the optimization process's current phase. Again, the inertia weight is recalculated, emphasizing the present phase's influence. This phase-dependent recalibration allows the algorithm to adapt its exploration and exploitation strategies according to the optimization progression, fine-tuning the search trajectory as it moves toward convergence.

(iv). Final Velocity Update

The fourth and final stage involves updating the velocities of particles while integrating the recalculated inertia weight. This stage considers the cumulative influence of the particle's experience, the global best, and the current phase.

This final velocity update optimizes the trade-off between exploration and exploitation while aligning with the optimization progress by utilizing the inertia weight adjusted throughout the algorithm's stages.

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3.3.6. Iterative Updates

The time required to perform the DPSO algorithm is expressed as Eq.(13) and Eq.(14).

$$R_{s,y}^{a} = \varpi R_{s,y}^{a-1} + \delta_1 \varphi_1 \odot \left(M_{s,y}^{a-1} - P_{s,y}^{a-1}\right) + \delta_2 \varphi_2 \odot \left(j_y^{a-1} - P_{s,y}^{a-1}\right) \quad (13)$$

And

$$P_{s,y}^{a} = \begin{cases} R_{s,y}^{a} & if\ b < 0.5 \\ P_{s,y}^{a-1} + R_{s,y}^{a} & if\ b \geq 0.5 \end{cases} \quad (14)$$

Where b respresents the random value between 0 and 1, i.e., $rand[0,1]$.

The total number of times the particle d_s falls into its local minimum is indicated as Z_s^a. In the beginning, when $a = 0$, all particles have a value of 0 for Z_s^a. The changes specified in Eq.(15) are incorporated to Z_s^a for $a \geq 1$.

$$Z_s^a = \begin{cases} Z_s^{a-1} + 1 & if\ g\left(P_{s,y}^{a}\right) > g\left(P_{s,y}^{a-1}\right) \\ 0 & otherwise \end{cases} \quad (15)$$

3.3.7. Reactive Adjustment and Particle Adaptation

The particle d_s will reach its local minimum at iteration a and continue to stay with the same value till t iterations. If $Z_s^a = t$, then the AP gets enabled, and the following steps are carried out for all d_s:

The AP component is shifted to the particle d_s as expressed in Eq.(16).

$$P_{s,y}^{a} = P_{s,y}^{a-1} \odot rand(R_{Min}, R_{Max}) \quad (16)$$

The AP determines the magnitude of the particle d_s and the velocity vector $\left|R_{s,y}^{a}\right|$. The set of velocities for individual particles has their local minima and a set of velocity vector magnitudes denoted by E. To determine N, the AP uses the data from set E, iteration a, and stage e_w. Eq.(17) is applied to calculate the value of N.

$$N = \begin{cases} \frac{max(E) - \min(E)}{\max(E)}, & a < \beta_1, |E| > 0 \\ \frac{max(E) - avg(E)}{\max(E)}, & \beta_1 \leq a < \beta_2, |E| > 0 \\ 0.1 + \left(0.8 \times \left(1 - \frac{a}{MaxIt}\right)\right), & \beta_2 \leq a < \beta_3, |E| > 0 \\ \frac{(MaxIT - a)}{MaxIT}, & \beta_2 \leq a < \beta_3, |E| > 0 \\ 0.8647, & |E| = 0 \end{cases} \quad (17)$$

The particle with the best possible global location at iteration a has a velocity of R_y^a. With the help of magnitude values $\left|R_y^{a-1}\right|$ and $\left|R_y^{a}\right|$ and a random number generator $l = rand(0,1)$, the AP revises the inertia weight value ϖ and the same is expressed in Eq.(18).

$$\varpi^a = \begin{cases} -N \times \frac{\left|R_y^a\right|}{\left|R_y^{a-1}\right|}, & l \leq 0.5 \\ N \times \frac{\left|R_y^a\right|}{\left|R_y^{a-1}\right|}, & l > 0.5 \end{cases} \quad (18)$$

Algorithm 3 provides the overall working of DPSO.

Input:

- E_s: Search space for a cluster U_s.
- y: Dimension of particle vectors.
- R_{Max}: Maximum search radius for velocities.
- R_{Min}: Minimum search radius for velocities.
- T: Swarm size.
- $MaxIt$: Maximum number of iterations.
- β_1,β_2,β_3: Threshold values for adaptive adjustment.
- t: Threshold for enabling Adjustment Phase (AP) mode.
- Fitness function $g\left(P_{s,y}^{a}\right)$.

Output:

- Optimized positions of particles within the search space.

Procedure:

Step 1: Initialization

- Initialize particles with random positions within the search space.
- Set the initial velocities of particles to zero.
- Initialize the best positions of particles with their initial positions.

Step 2: Algorithm Execution (for each iteration a):

Repeat Step 3 to

Step 3: Update each particle's velocity using cognitive and social components:

- Calculate the cognitive component based on the difference between the particle's current and best positions.
- Calculate the social component based on the difference between the particle's current and global best positions.
- Update the particle's velocity using inertia weight, cognitive, and social components.

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Step 4: Update each particle's position using its velocity

Step 5: Update Z_s^a for each particle

- If the fitness of the current position is better than the fitness of the previous position, increment Z_s^a.

Step 6: If Z_s^a reaches the threshold t, activate AP mode

- Randomly adjust the particle's position within the search space.
- Calculate a value N based on thresholds β_1,β_2,β_3, and the number of particles with better fitness.
- Update the inertia weight ϖ^a based on N

Step 7: Evaluate the fitness of each particle's new position and update the global best position.

Step 8: Termination

- Repeat the algorithm for a total of $MaxIt$ iterations.

Algorithm 3 DPSO

3.4. Difference

The significant differences between PSO and DPSO are provided in Table 2.

Table 2 Difference between PSO and DPSO

Parameter	PSO	DPSO
Inertia Weight	Fixed weight throughout.	Adapts inertia weight based on N.
Global Best Update	Fitness-based global best update.	Updates global best position based on fitness improvements.
Adaptive Mechanism	Lacks adaptive adjustments.	Integrates adaptive exploration-exploitation strategy based on Z_s^a and t.
Combatting Convergence	Susceptible to early convergence.	Designed to mitigate early convergence through adaptability.
Speed Update	Relying on personal and social experiences.	Integrating personal, social, and adaptive experiences.
Exploration Range	Fixed radius values	Dynamic radius values
Performance Evaluation	Comparing current and previous states.	Evaluating fitness values for progress.
Global Best Update	Updating based on improved individuals.	Incorporating better fitness for global updates.

3.5. Fusion of DPSO and GAOMDV

Fusing the Gaussian-AOMDV routing protocol can lead to a more robust and efficient routing algorithm for wireless ad hoc networks. This fusion leverages the strengths of both approaches to enhance network performance, adapt to dynamic changes, and optimize route selection. The pseudocode of DPSO-GAOMDV is provided in Algorithm 4.

Step 1: Initial Route Discovery

- GAOMDV: Nodes initiate route discovery based on Gaussian predictions of link stability. Routes are established using the most stable links.
- DPSO: Particles can be used to explore initial routes with the consideration of predicted link stability as a fitness metric.

Step 2: Link Stability Prediction

- GAOMDV: Continuously predicts link quality using Gaussian distribution.
- DPSO: Utilizes DPSO's adaptive mechanism to adjust particle behavior based on the predicted link stability.

Step 3: Adaptive Routing

- GAOMDV: Routes adapt to predicted link failures.
- DPSO: Adaptive behavior helps particles explore alternative routes in response to changing link stability predictions.

Step 4: Path Optimization

- GAOMDV: Focuses on stable links, reducing route maintenance.

- DPSO: Optimizes routes based on dynamic factors, including predicted link stability and network parameters.

Step 5: Route Maintenance

- GAOMDV: Minimizes route updates due to proactive link stability prediction.
- DPSO: Further reduces route updates by intelligently adapting particle movements.

Step 6: Robustness Enhancement

- Combined Approach: The fusion enhances overall network robustness by proactively adapting routes to predicted and real-time changes.

Algorithm 4 DPSO-GAOMDV

4. SIMULATION SETTING

Table 3 Simulation Setting

Parameter	Values
Channel	WirelessChannel
Data type	Varying Bit Rate (VBR)
MAC protocol	IEEE 802.11p
Network interface	WirelessPhy
Number of nodes	6 to 60
Packet size	1000 bytes
Propagation model	Two Ray Ground
Simulation Object	Urban area, Highway scenario
Simulation area	12 km × 6 km
Simulation time	300 seconds
Transport protocol	TCP
Transmission power	20 dBm (100 mW)
Transmission range	300 meters
Vehicles speed	Average: 25 m/s, Max: 35 m/s

NS-3, the Network Simulator 3, is a pioneering platform that propels network simulation into the future. Tailored for researchers, engineers, and educators, NS-3 empowers them to unravel the complexities of communication networks. Its precise emulation of diverse network topologies, including wireless and vehicular scenarios, makes it an indispensable tool. NS-3's modular structure allows customization, enabling the creation of novel protocols and models. It serves as an extensive laboratory for performance evaluation and refining networking solutions. Bolstered by a vibrant community, NS-3 offers a wealth of resources and collaboration, fostering knowledge exchange. NS-3 is not just a simulator; it's a catalyst for innovation, pushing the boundaries of network understanding and technology evolution. The setting for evaluating this research work against the state-of-the-art routing protocols is provided in Table 3.

5. RESULTS AND DISCUSSION

5.1. Packet Delivery and Drop Ratio

Packet Delivery Ratio is a performance metric that measures the percentage of packets successfully delivered from the source to the destination out of the total packets generated. A higher PDR indicates better performance as it signifies a higher proportion of packets successfully reaching their intended destination. It is given by the Eq.(19):

$$Packet\ Delivery\ Ratio = \frac{No.of\ Packets\ Received\ at\ Destination}{Total\ No.of\ Packets\ Sent} X100 \quad (19)$$

Packet Drop Ratio is a performance metric that measures the percentage of packets that were dropped or lost during transmission. A lower Packet Drop Ratio is desirable as fewer packets are lost or discarded during transmission. It is given by the Eq.(20).

$$Packet\ Drop\ Ratio = \frac{No.of\ Packets\ Received\ at\ Destination}{Total\ No.of\ Packets\ Sent} X100 \quad (20)$$

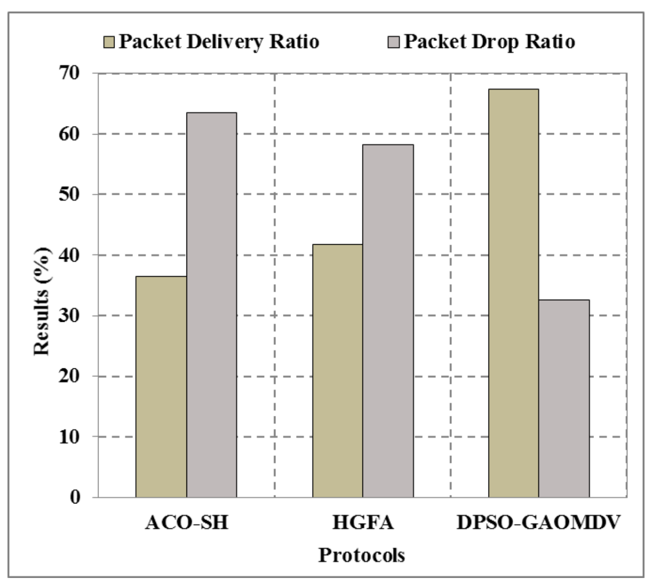

Figure 1 Packet Delivery and Drop Ratio

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The results presented in Figure 1 show the Packet Delivery Ratio and Packet Drop Ratio for three different routing protocols: ACO-SH, HGFA, and DPSO-GAOMDV. Each protocol's unique characteristics or mechanisms contribute to their respective results. Table 4a and Table 4b indicates the appropriate values of Figure 1.

Table 4a Packet Delivery Ratio

Nodes	ACO-SH	HGFA	DPSO-GAOMDV
6	47.08	50.45	73.82
12	45.06	47.81	73.14
18	42.75	45.02	72.19
24	42.07	44.39	69.56
30	40.39	43.56	67.75
36	35.18	41.64	66.84
42	30.83	39.66	65.22
48	29.28	37.01	64.03
54	27.26	35.15	61.86
60	24.43	33.35	59.74
Average	36.43	41.80	67.42

Table 4b Packet Drop Ratio

Nodes	ACO-SH	HGFA	DPSO-GAOMDV
6	52.92	49.55	26.18
12	54.94	52.19	26.86
18	57.25	54.98	27.81
24	57.93	55.61	30.44
30	59.61	56.44	32.25
36	64.82	58.36	33.16
42	69.17	60.34	34.78
48	70.72	62.99	35.97
54	72.74	64.85	38.14
60	75.57	66.65	40.26
Average	63.57	58.20	32.58

ACO-SH appears to have the lowest Packet Delivery Ratio among the three protocols. This could be due to the nature of ant colony optimization, where the behavior of artificial ants might not optimally adapt to dynamic network changes. Self-healing mechanisms in this protocol might focus more on recovery than optimizing the overall packet delivery process, leading to a comparatively lower PDR. The higher Packet Drop Ratio suggests that packet loss due to suboptimal path choices or insufficient self-healing adjustments might be more prevalent. HGFA shows a better Packet Delivery Ratio compared to ACO-SH. Using hybrid genetic and firefly algorithms could contribute to more efficient path selection and optimization, improving packet delivery. The genetic algorithm's evolutionary mechanisms and the firefly algorithm's attraction-based characteristics might collectively enhance the routing decisions. The Packet Drop Ratio is moderate, indicating that the hybrid approach effectively reduces packet loss.

DPSO-GAOMDV exhibits the highest Packet Delivery Ratio among the three protocols. This can be attributed to the integration of PSO and Gaussian AOMDV routing. PSO's cooperative search and optimization abilities might enable the protocol to find efficient paths more effectively. The Gaussian AOMDV's multipath approach could enhance reliability. The lower Packet Drop Ratio suggests that this protocol's combination of optimization and multipath routing leads to fewer dropped packets. The differences in Packet Delivery Ratio and Packet Drop Ratio among the protocols can be linked to the unique characteristics of each protocol. Factors such as optimization algorithms, adaptability to network changes, and multipath routing strategies play pivotal roles in determining the protocols' effectiveness in delivering packets successfully while minimizing packet loss.

5.2. Throughput

Throughput is a performance metric that measures the rate at which data is successfully transmitted from source to destination over a network. It represents the amount of data transmitted in a given time interval. Throughput is typically measured in kilobits per second (Kbps). Higher throughput values indicate that the network can transmit data more efficiently and faster, resulting in better performance. Mathematically, throughput can be defined as Eq.(21).

$$Throughput = \frac{Total\ Amount\ of\ Data\ Received}{Total\ Time\ taken\ for\ Transmission} \times 100 \tag{21}$$

Figure 2 illustrates the throughput results for three routing protocols: ACO-SH, HGFA, and DPSO-GAOMDV. The unique characteristics and mechanisms of each protocol contribute to their respective throughput results provided in Table 5.

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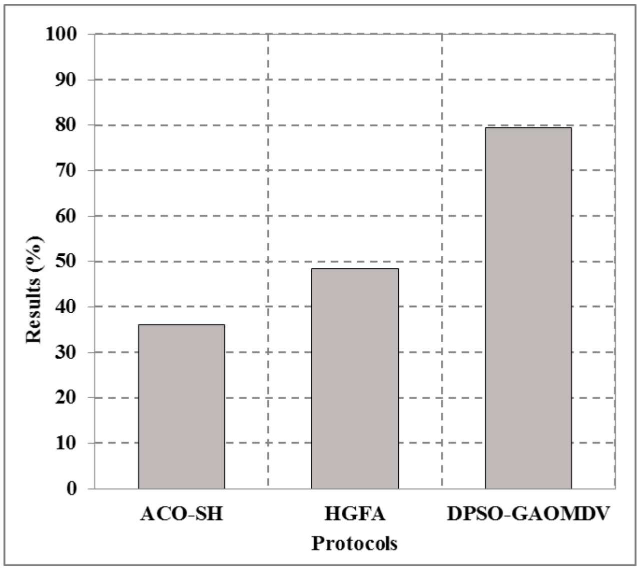

Figure 2 Throughput

ACO-SH exhibits the lowest throughput values among the three protocols. This can be attributed to the inherent characteristics of the ant colony optimization algorithm and the self-healing mechanism. While ant colony optimization effectively finds paths, it might introduce additional overhead due to the pheromone-based communication and exploration process. Moreover, though beneficial for network resilience, the self-healing aspect can lead to longer route discovery times and increased latency.

These factors collectively result in lower throughput, as the focus on robustness and recovery comes at the expense of raw data transmission speed. The moderate throughput values observed with HGFA are influenced by its hybrid approach that integrates genetic and firefly algorithms. The genetic algorithm's evolutionary mechanisms enable the protocol to converge towards optimized paths over time.

The firefly algorithm's attraction-based nature aids in effective path exploration. However, while these algorithms enhance path selection, they may not thoroughly prioritize data transmission speed. The moderate throughput values can be attributed to a trade-off between optimization and transmission efficiency.

DPSO-GAOMDV demonstrates the highest throughput values among the three protocols. This can be attributed to the incorporation of PSO and Gaussian AOMDV routing. PSO's cooperative optimization capabilities facilitate the discovery of efficient paths for data transmission. The Gaussian AOMDV's multipath approach enhances reliability and allows for concurrent data transmission. The protocol's focus on optimization and efficient path diversification contributes to the higher throughput values. The emphasis on optimizing paths for speed while maintaining reliability results in superior data transmission rates.

Table 5 Throughput

Nodes	ACO-SH	HGFA	DPSO-GAOMDV
6	31.46	44.23	71.47
12	31.97	44.77	73.62
18	32.64	46.32	75.98
24	33.76	46.62	76.26
30	34.43	48.06	80.65
36	35.13	48.87	80.97
42	39.16	50.64	81.12
48	39.96	50.74	82.15
54	40.31	51.77	84.69
60	40.92	52.47	87.35
Average	35.974	48.449	79.425

The differences in throughput results among the routing protocols directly reflect their unique characteristics and mechanisms. The balance between optimization, self-healing, and path diversification is pivotal in determining data transmission efficiency. While some protocols prioritize robustness and recovery, others balance optimization and transmission speed. The protocol with the optimal balance achieves higher throughput values, signifying its capacity to transmit data more efficiently and rapidly.

5.3. Delay

Delay is a critical performance metric in networking that measures the time data packets travel from the source to the destination through a network. It indicates the time delay experienced by data as it traverses various network components, such as routers, switches, and links. Delay is typically measured in milliseconds (ms) and encompasses various components, including processing, queuing, transmission, and propagation delays. A lower delay value indicates faster data transmission and a more responsive network, crucial for real-time applications like voice and video communication. Mathematically, the total delay experienced by a packet can be defined as the sum of these individual components, and Eq.(22) represents the same.

$$Total\ Delay = ProD + QueD + TraDelay + PropD \tag{22}$$

Where $ProD$ indicates Processing Delay, $QueD$ indicates Queuing Delay, $TraDelay$ indicates Transmission Delay, and $PropD$ indicates Propagation Delay.

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The delay values for ACO-SH are the highest among the three protocols. This can be attributed to the inherent characteristics of ant colony optimization and the self-healing mechanism. The iterative nature of ant colony optimization may introduce processing and queuing delays as the protocol explores various paths before making a decision. While enhancing network resilience, the self-healing mechanism can lead to longer route discovery times and increased queuing delays. These factors contribute to the higher delay values, as the protocol emphasizes network robustness more than minimizing data transmission time. HGFA demonstrates moderate delay values. The hybrid approach involving genetic and firefly algorithms aims to balance optimization and minimize delays. While these algorithms contribute to efficient path selection, they may introduce some processing and queuing delays during optimization. The protocol's ability to find reasonably optimized paths while considering transmission efficiency results in moderate delay values.

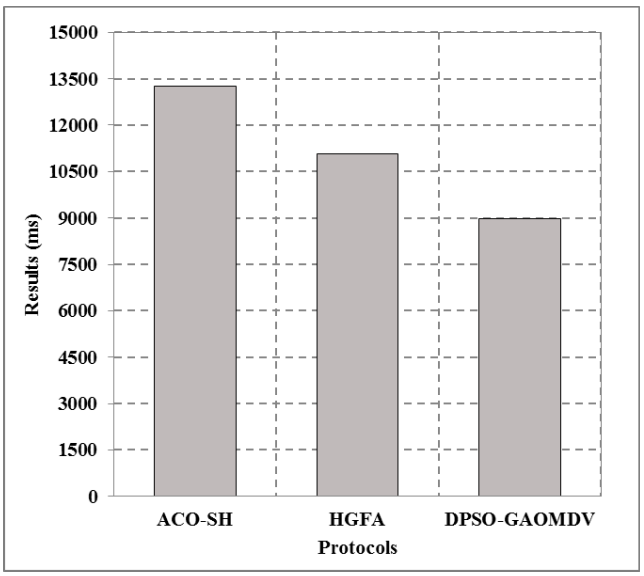

Figure 3 Delay

DPSO-GAOMDV exhibits the lowest delay values among the three protocols. This is due to PSO integration and Gaussian AOMDV routing. PSO's optimization capabilities enable the protocol to identify paths with lower delays. Additionally, the multipath nature of Gaussian AOMDV helps reduce propagation delays by utilizing multiple paths concurrently. The protocol's focus on optimization and efficient path diversification leads to the lowest overall delays.

The delay results reflect the interplay between each protocol's optimization mechanisms, path selection strategies, and their prioritization of network resilience versus data transmission efficiency. While some protocols lean toward robustness and recovery, others balance optimization and delay reduction. The protocol achieving the optimal balance achieves the lowest delay values, signifying faster data transmission and a more responsive network. Table 6 provides the result values of Figure 3.

Table 6 Delay

Nodes	ACO-SH	HGFA	DPSO-GAOMDV
6	12837	10285	7644
12	12872	10348	7670
18	12894	10666	7723
24	12931	10723	8949
30	13149	10874	9166
36	13364	10934	9512
42	13472	11057	9549
48	13588	11461	9590
54	13635	11730	9593
60	13922	12774	10233
Average	13266.4	11085.2	8962.9

5.4. Energy Consumption

Energy Consumption is a crucial performance metric in networking that quantifies the energy consumed by network devices and components during data transmission and communication. It reflects the efficiency of a network in utilizing energy resources for its operations. Energy consumption is particularly significant in wireless and mobile networks where limited battery capacities often constrain devices. Reducing energy consumption is essential to extend the operational lifetime of network devices and minimize the need for frequent battery replacements or recharging. Mathematically, energy consumption can be defined in Eq.(23).

$$\text{Energy Consumption} = \text{Power Consumption} \times \text{Time} \tag{23}$$

Where $Power\ Consumption$ represents the rate at which energy is consumed by a device, $Time$ denotesthe duration of data transmission or communication. Figure 4 presents the energy consumption results for three routing protocols: ACO-SH, HGFA, and DPSO-GAOMDV. Each protocol's unique characteristics and mechanisms contribute to their respective energy consumption results, as expressed in Table 7.

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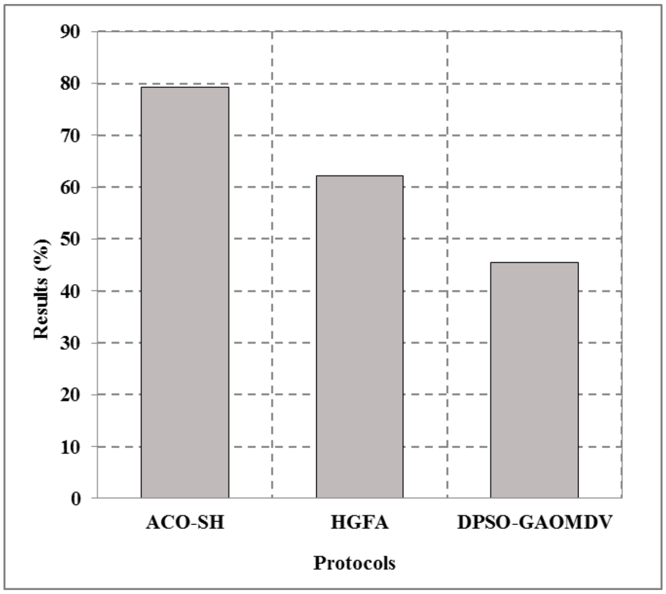

Figure 4 Energy Consumption

ACO-SH demonstrates the highest energy consumption values among the three protocols. This can be attributed to ant colony optimization and the self-healing mechanism. Ant colony optimization involves iterative exploration and path selection, which may lead to higher power consumption due to repeated computation. The self-healing aspect might also contribute to energy inefficiency by prolonging route discovery and maintenance processes, consuming more energy over time. HGFA exhibits moderate energy consumption values. The hybrid approach involving genetic and firefly algorithms balances optimization and energy efficiency. While these algorithms introduce some computational overhead, the protocol's focus on finding reasonably optimized paths helps manage power consumption. The protocol aims to optimize paths while mindful of energy constraints, leading to moderate energy consumption values.

DPSO-GAOMDV demonstrates the lowest energy consumption values among the three protocols. Integrating PSO and Gaussian AOMDV routing contributes to optimized path selection and reduced power consumption. PSO's optimization capabilities enable the protocol to find energy-efficient paths. The multipath nature of Gaussian AOMDV can distribute energy usage across multiple paths, minimizing the strain on individual links and devices. The protocol's optimization focuses and path diversification result in lower overall energy consumption.

The differences in energy consumption among the protocols directly result from their unique characteristics and mechanisms. The trade-off between optimization, self-healing, and energy efficiency influences power consumption during data transmission. While some protocols prioritize robustness and recovery, others emphasize optimization and energy-efficient routing. The protocol that strikes the right balance achieves the lowest energy consumption values, indicating efficient utilization of energy resources.

Table 7 Energy Consumption

Nodes	ACO-SH	HGFA	DPSO-GAOMDV
6	70.855	52.738	39.504
12	71.964	54.29	39.97
18	74.249	56.707	40.56
24	77.561	57.329	41.443
30	78.621	57.861	43.369
36	80.817	65.25	48.045
42	82.981	65.855	49.229
48	84.152	68.085	49.511
54	85.102	70.31	51.113
60	86.975	72.505	51.8
Average	79.328	62.093	45.454

5.5. Network Lifetime

Network Lifetime is a crucial performance metric in wireless and mobile networks that estimates the duration for which the network can operate effectively without needing to replace or recharge network nodes' energy sources (typically batteries).

It reflects the sustainability of a network in terms of energy consumption and efficiency. Maximizing network lifetime is essential to ensure continuous and reliable network operation, mainly when nodes have limited energy resources. A longer network lifetime indicates efficient energy utilization and a more sustainable network. Mathematically, network lifetime can be defined in Eq.(24):

$$Network\ Lifetime = \frac{Total\ Available\ Energy}{Average\ Energy\ Consumption\ per\ Unit\ Time} \times 100 \quad (24)$$

Where $Total\ Available\ Energy$ indicates the total energy available in the network, and $Average\ Energy\ Consumption\ per\ Unit\ Time$ represent the average rate at which energy is consumed by the network.

Figure 5 presents the network lifetime results for three routing protocols: ACO-SH, HGFA, and DPSO-GAOMDV. Each protocol's unique characteristics and mechanisms contribute to their respective network lifetime results, which are provided in Table 8.

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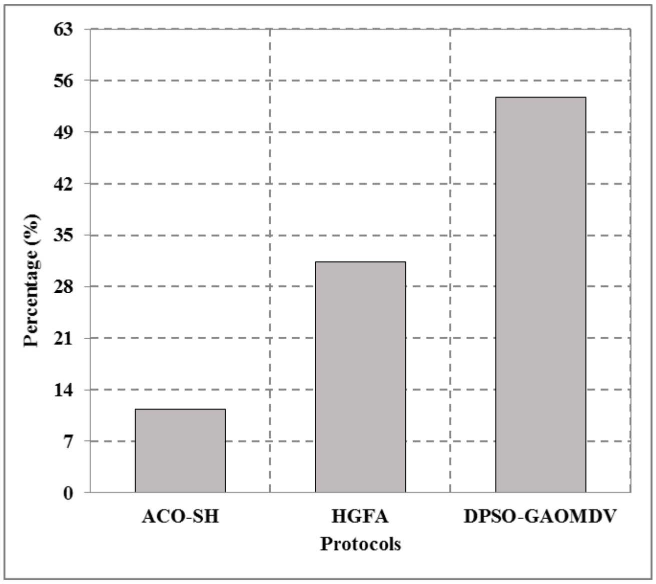

Figure 5 Network Lifetime

ACO-SH demonstrates the shortest network lifetime among the three protocols. This can be attributed to the characteristics of ant colony optimization and the self-healing mechanism. Ant colony optimization involves iterative exploration of paths, leading to repeated computations that consume energy. Moreover, while enhancing network resilience, the self-healing mechanism may prolong route discovery and maintenance, contributing to higher energy consumption.

These factors collectively result in a shorter network lifetime, as the protocol prioritizes network robustness and recovery over energy conservation. HGFA presents a moderate network lifetime. The hybrid approach balances optimization and energy efficiency by integrating genetic and firefly algorithms. While these algorithms introduce some computational overhead, the protocol focuses on identifying reasonably optimized paths that effectively manage energy consumption. The protocol's optimization goal is influenced by energy constraints, leading to a compromise between network longevity and optimized path selection, resulting in a moderate network lifetime.

DPSO-GAOMDV exhibits the most extended network lifetime among the three protocols. Integrating PSO and Gaussian AOMDV routing contributes to optimized path selection and efficient energy consumption. PSO's optimization capabilities enable the protocol to discover energy-efficient paths. The multipath nature of Gaussian AOMDV balances energy usage across multiple paths, preventing undue energy depletion. The protocol's optimization focus and energy-efficient routing strategies culminate in the most extended network lifetime.

Table 8 Network Lifetime

Nodes	ACO-SH	HGFA	DPSO-GAOMDV
6	18.71	44.43	60.17
12	17.86	43.59	59.64
18	15.04	40.14	58.14
24	12.61	38.46	57.29
30	11.53	31.39	56.26
36	10.63	25.04	55.99
42	8.33	23.62	49.61
48	7.68	23.04	48.59
54	6.12	21.76	47.38
60	4.41	21.69	44.55
Average	11.291	31.316	53.761

The network lifetime results result from the intricate interplay between the protocols' unique characteristics and mechanisms. The equilibrium between optimization, self-healing, and energy efficiency significantly influences energy consumption and, consequently, the network's operational duration. While some protocols emphasize robustness and recovery, others centre around energy-efficient routing and path optimization. The protocol that adeptly balances these factors achieves the most extended network lifetime, indicating an optimal utilization of energy resources and a sustainable network operation over an extended period.

6. CONCLUSION

The emergence of Stochastic VANETs (SVANETs) has ushered in a new era of challenges and complexities in vehicular communication. The uncertainties brought about by dynamic traffic patterns, varying communication landscapes, and unpredictable link qualities have necessitated innovative routing solutions. The "Decisiveness PSO-Based Gaussian AOMDV (DPSO-GAOMDV) Routing Protocol" is a potential routing protocol in this domain. By fusing the predictive capabilities of Gaussian-Anticipatory On-Demand Distance Vector (GAOMDV) routing with the dynamic adaptability of Particle Swarm Optimization (PSO), the DPSO-GAOMDV protocol offers a robust approach to addressing the intricate challenges of SVANET routing. As demonstrated through extensive simulations under realistic stochastic vehicular scenarios, its performance showcases its ability to optimize routing decisions while reducing maintenance overhead and improving network stability. The DPSO-GAOMDV protocol's potential to navigate the uncertainties of SVANETs and provide efficient and resilient routing solutions

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underscores its relevance in enhancing vehicular communication, safety, and overall network performance in dynamically evolving environments.

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RESEARCH ARTICLE

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