SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/https://doi.org/10.14445/23488379/IJEEE-V12I2P114

Volume 12 Issue 2, 124-136, February 2025

Original Article

Dynamic Learning Network-Distributed Exploration: Advancements in Hybrid Swarm Intelligence Algorithm for Congestion Control in Vehicular Ad-Hoc Networks

Kiran Kumar Jajala[1], Reddaiah Buduri[2]

[1,2]*Department of Computer Science & Technology, Yogi Vemana University, Andhra Pradesh, India.*

[2]*Corresponding Author : prof.reddaiah@yvu.edu.inz*

Received: 12 December 2024 Revised: 11 January 2025 Accepted: 08 February 2025 Published: 22 February 2025

Abstract *- At the Nexus of Intelligent Transportation Systems (ITS), Vehicular Ad-hoc Networks (VANETs) have become a quickly developing field, highlighting the necessity of a resilient and reliable VANET architecture to support increasing vehicle densities. This study has proposed a new technique, namely a Hybrid Swarm Intelligence Algorithm (HSIA), that mixes distributed exploration approaches rooted in hybrid swarm intelligence paradigms and dynamic learning mechanisms. Our proposed approach, which builds on the ideas of Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO), combines network-distributed communication, dynamic learning rates, and reinforcement learning approaches to improve algorithm performance and adaptability. We provide novel equations for adaptive pheromone updates with Dynamic Learning, Collective Exploration with Network-Distributed Pheromone Update and Adaptive Exploration-Exploitation Trade-off with Reinforcement Learning. Our experimental results on VANETS show that our method is more controlling and versatile than conventional ACO or ABC algorithms when striving for quicker convergence rates and higher-quality results. MATLAB simulations are used for the experimental validation of the HSIA technique, which shows improved performance over conventional ACO and ABC. Comparing HSIA to ACO, the packet delivery ratio and throughput increased significantly to 1.09 percent and 1.48 percent, respectively. Compared to ABC, HSIA showed an incredible increase in its packet delivery ratio and throughput of 15.94% and 9.87%, respectively. HSIA experienced a 17.25% lower end-to-end delay compared to ABC. On the other hand, HSIA's end-to-end delay was 5.59% lower than that of ACO. Critical performance metrics showing this improvement include packet delivery ratio, throughput, and end-to-end delay.*

Keywords *- Vehicular Ad-hoc Networks, Artificial Bee Colony Optimization, Ant Colony Optimization, Reinforcement learning, Swarm intelligence.*

1. Introduction

The VANETs are specialized mobile ad hoc networks created mainly to enable vehicle communication in dynamic transportation environments [1, 2]. For commuters, congestion in VANETs poses serious obstacles because it lengthens travel times, increases fuel consumption, and lowers road safety [3]. On-Board Units (OBUs), Roadside Units (RSUs), sensors and vehicles are all part of the VANETs architecture. In addition, the RSU can communicate with other RSUs and neighboring vehicles [4].

Vehicle-to-Vehicle (V2V) systems enable direct data interchange between nearby vehicles to enable real-time information sharing for collision avoidance and cooperative driving applications. On the other hand, the interchange of data between moving vehicles and the roadside infrastructure is referred to as vehicle-to-Infrastructure (V2I) communication [5-8]. Various sensors positioned across the surroundings are used in Vehicle-to-Sensor (V2S) communication. Vehicles could receive information that can be sent to them through traffic cameras, sensors in other vehicles, and sensors on roadsides. Smart device connectivity can be extended with Vehicle-to-Device (V2D) communication. Smartphones and vehicles can communicate. For example, a driver's Smartphone and a connected vehicle can synchronize to enable smooth, hands-free operation [9].

The ACO algorithm aims to find the best way to optimize search results using a probabilistic approach. The algorithm was presented by Marco Dorigo in 1992. Dorigo derived the idea from ants exploring paths when searching for food [10]. Karaboga from Turkey's Erciyes University introduced the ABC swarm intelligence algorithm in 2005. The effectiveness of this process was analyzed in 2007. The intelligent foraging behavior of honeybees served as an inspiration for the algorithm [11-13]. The collective behavior of social insects has served as an inspiration for the development of swarm intelligence algorithms, which are now very effective tools for resolving challenging optimization issues. Two of these algorithms, ABC and ACO, have attracted much interest due to their ability to search solution spaces and effectively identify superior solutions. In this study, we provide a unique technique that builds on the foundations of ACO and ABC to develop HSIA that can perform network-distributed exploration and dynamic learning. We want to improve the effectiveness and flexibility of these algorithms to deal with optimization issues in several areas.

To achieve this, we use decentralized exploration tactics alongside dynamic learning mechanisms. The contributions that make our work major include adaptive pheromone updating formulas, networked communication for collaborative exploration, and reinforcement techniques that enable trade-offs between exploration and exploitation in adaptive learning. In response to learning goals and problem changes, this algorithm can now modify the searching procedure to achieve significant solutions towards exploration of a larger area for solutions as well as convergence on better alternatives.

Congestion control is important for VANETs to ensure that V2V communication is reliable and efficient. In these dynamic environments, HSIA, which combines dynamic learning and network-distributed exploration, provides a powerful solution to congestion problems. The system can make real-time routing adjustments in response to shifting traffic conditions and network dynamics using dynamic learning methods. Because vehicles can change their path, they can select other routes, reducing areas where a lot of vehicles pass through, which leads to increased effectiveness of the highway system generally. Also, peer-to-peer communication through a network that is not centralized enables cooperative measures for preventing jams while sharing data related to them.

Vehicles can use general traffic information to make informed decisions on routing, making congestion control strategies more efficient in such a decentralized approach [14]. It is also possible to have an adaptive congestion management strategy in which dynamic is feasible using reinforcement learning methods based on network performance criteria. Further, in VANETs, vehicles can learn and adapt to their environment over time, thus aiding with resource allocation efficiency and traffic jam modulation. Hybrid swarm intelligence algorithms can be leveraged to increase the performance and dependability of communication in VANETs, leading to more dependable and efficient congestion management systems. In conventional VANET, congestion control solutions are not very flexible in response to changing traffic conditions, have centralized control, which limits scalability, and have a high communication cost, which results in inefficient resource allocation and slows reaction times to congestion environments. These constraints need to be addressed to provide reliable communication and efficient traffic management in VANETs [15].

1.1. Challenges and Issues of ACO and ABC Algorithms

- Achieving equilibrium between exploration and exploitation: The simultaneous exploration and exploitation of both the ACO and ABC algorithms are required to reach this equilibrium at their operations in a way that will yield the best results.
- Early Convergence: ACO and ABC algorithms have difficulty with early convergence. This is when the algorithms stop looking for the best solution and start settling for any solution within a brief time frame. To avoid this problem from happening prematurely, the methods need some guidance on what they should do.
- Sensitivity of Parameters: ABC needs the fine-tuning of its ants' population, whereas ACO requires the determination of the evaporation ratio of its pheromones. There is a high degree of sensitivity to parameter settings, and fine-tuning is often necessary for these algorithms in practice.
- Speed of Convergence: This challenge is widely acknowledged in the ACO and ABC algorithms, as both approaches can have slow convergence speeds, especially in intricate search spaces. The problem remains how to increase the convergence rate without compromising the quality of solutions for these two methods.
- Scalability: Both algorithms, ABC and ACO, may come up with problems related to optimization problems on a larger scale.

1.2. Motivation

VANETs present distinct challenges and requirements that motivated the algorithm development described in “Dynamic Learning and Network-Distributed Exploration: Advancements in Hybrid Swarm Intelligence Algorithm”. In dynamic and unpredictable contexts, VANETs provide wireless V2V communication for vital information sharing in applications like infotainment, traffic management, and collision avoidance. Although VANETs have a great capability for effective communication and congestion management, their dynamic nature serves as a limiting factor.

The major challenge VANETs face is traffic because it changes with respect to traffic flow, accidents, and road states. The failure to adapt may result in inefficient routing and increased communication delay times in the traditional congestion control algorithms. Attempts to manage congestion are made more difficult by the fact that many VANET applications are real-time, meaning they need consistent connectivity and low latency. The discussed solution was developed using network-distributed exploration and dynamic learning to address these challenges.

1.3. Contribution

The algorithm featured in "Dynamic Learning and Network-Distributed Exploration: Advancements in Hybrid Swarm Intelligence Algorithm" is a notable breakthrough intended to resolve the complex problems linked to VANETs. Technology removes congestion hotspots and communication delays by allowing vehicles to flexibly change their path choices because of dynamic learning techniques that respond to the varying traffic conditions and network dynamics. Besides, adding network-embedded research enhances network scalability with more distributed vehicle communication, congestion data sharing, and cooperative ways to avoid it.

The algorithm continuously modifies its communication settings to accommodate different traffic flows and congestion levels. This makes it possible to both save resources effectively and improve communication dependability besides increasing throughput. By doing this, redistribution of resources is facilitated. Its dynamic congestion management strategies and adaptive routing decisions, particularly in safety-relevant tasks such as the organization of urgent vehicle transport and accident avoidance, ensure that the algorithm greatly enhances safety, reliability, and overall network performance in VANETs.

1.4. Organization of Work

The following structure guides the organization of this paper. In Chapter 1, a basic overview of VANETs, the main issues, and difficulties with ABC and ACO algorithms are covered. The discussion revolves around the implementation of HSIA and its motivation behind the problems mentioned earlier. The background information and literature on earlier studies on ABC and ACO algorithms are included in Chapter 2. Newly designed HSIA is illustrated in Chapter 3. Chapter 4 presents the comprehensive outcomes of the simulation.

2. Literature Survey

Several hybrid algorithms based on swarm intelligence can prevent congestion within VANETs by drawing from various optimization strategies.

Due to their ability to blend the functionality of various optimization techniques, resulting in better strength and efficiency, researchers are getting more and more interested in hybrid swarm intelligence algorithms. Complex and dynamic environments like VANETs need sophisticated performance that can rarely be achieved through a single-method solution, which is what makes these hybrid approaches preferable. Recent developments and real-world implementations of such methodologies are reviewed in this paper to show their capabilities in adapting to changing traffic scenarios and optimizing network efficiency.

C. Kumuthini et al. [16] presented Ant with Artificial Bee Colony Techniques (AABC) algorithm, which yields more improvement, especially regarding energy consumption. Using ABC techniques, the VANET determines the optimal path scheduling techniques through the ant. Processing time, delay, throughput, and channel utilization are the parameters that are considered in this technique. The foundation of the AABC algorithm is two fundamental methods: variation and selection. Various search space locations are evaluated for availability, while historical data is utilized as a guarantee by the selection procedure. The AABC algorithm improves the quality of solutions by incorporating a more efficient local search mechanism. The simulation results show that the suggested methods will provide the highest possible level of service compared to the current methods.

NingGuo et al. [17] proposed an improved hybrid ACO algorithm to reduce the overall mileage of the Multi-Compartment Vehicle Routing Problem (MCVRP). The first step is to construct a probabilistic model that considers both related customer blocks and customer variations to guide the algorithm search towards high-quality regions. Afterwards, initial individuals are created for the probabilistic model through heuristic rules, which help find high-quality areas very quickly. Furthermore, the exploitation of the promising areas is regulated by a new local exploration using geometry optimization. Two distinct kinds of Variable Neighborhood Descent (VND) methods are created to enhance the local exploitation capability even further. These strategies are based on the initial move strategy and the speed-up search approach. Numerical experiment findings based on benchmark datasets ultimately show the efficacy and efficiency of an improved hybrid ACO algorithm.

Sengathir Janakiraman et al. [18] proposed the Hybrid ACO and ABC Optimization Algorithm-based Cluster Head Selection method as an efficient way to choose a cluster head, effectively removing the restrictions of both ACO and ABC. Extensive combinations of factors considered ideal are presented in this proposed technique, along with an examination of the complete set of factors critical in determining an ideal cluster head in the Internet of Things. Consequently, the exhaustive combinations of components found by ACO are assumed to represent the first potential solutions for the ABC algorithm. Moreover, ACO employee bee agents assist with the initial exploitation stage and forecast the precision of every potential solution. Additionally, following the first degree of exploitation, the observer bee agents calculate the fitness and objective function across the first possible options. In the proposed system, these "onlooker bee" agents decide which set of parameters goes into selecting the optimal cluster head. The estimated combination of factors is again inputted into the ACO to identify the ideal combination of factors responsible for effective cluster head selection. This process is conducted globally. According to the experimental study's findings, the proposed approach efficiently outperforms the benchmarked cluster head selection strategies regarding throughput, residual energy, alive nodes and dead nodes percentage.

Anxiang Ma et al. [19] presented an Adaptive Hybrid ACO Algorithm (A_HACO) for solving hybrid attribute classification problems and obtaining intelligible categorization rules simultaneously. It can solve classification problems with effectiveness. The ACO is integrated with the ABC optimization strategy. The A_HACO algorithm for classification issues incorporates the ABC optimization process into the ACO process. This allows the algorithm to gradually create accurate and understandable classification rules. Four candidate rule evaluation functions- the Klosgen measure, F-measure, M-estimate, and Q+ are taken into consideration in A_HACO. The algorithm's capacity to adaptively select the appropriate rule evaluation function can greatly improve classification accuracy. The experiment outcomes show that the proposed approach works better in terms of accuracy and applicability.

M. Kefayat et al. [20] present the hybrid ACO-ABC algorithm, which combines the best features of the ACO and ABC algorithms to determine the ideal location and size of Distributed Energy Resources (DERs) on distribution networks. By using location optimization and size optimization mechanisms, the proposed approach combines the advantages of the ABC and ACO methods' global and local search capabilities, respectively. Furthermore, a set of non-dominated solutions is produced using a multi-objective ABC and saved in an external archive. This work solves the optimization problem in a stochastic environment using the efficient Point Estimate Method (PEM). The IEEE 33- and 69-bus distribution systems are used to test the proposed algorithm. Compared to other evolutionary optimization techniques, the outcomes show the ability and efficacy of the proposed process.

Changsheng Zhang et al. [21] proposed an algorithm known as the hybrid ABC, which incorporates the ACO mechanism into the ABC optimization process to address the large-scale service problem. This algorithm models the search area depending on a grouping process using flexible self-adaptive varying construct graphs and employs a skyline query procedure to narrow down the pool of candidates for each service class; if quality candidates are retained, this can drastically cut down on the number of candidates to find. This method builds a self-adaptive dynamic cluster network, focuses on the large-scale service choosing an issue and is applied to predict the search-critical subarea. Lastly, using a variety of standard real datasets and synthetically created datasets, this approach is tested experimentally and contrasted with a few related service selection algorithms recently proposed. In terms of the magnitude of the solutions, the results are quite encouraging.

Abba SugandaGirsang et al. [22] proposed a new hybrid algorithm named HABCO, a combination of Ant Colony System (ACS), Bee Colony Optimization (BCO), and ELU-Ants. This tour portion can be recognized as the BCO stage, which includes a few cities. It is anticipated that the stage-tour agent will evaluate the quality agent. Bees return to the hive on BCO after traveling one stage, which is divided into three types according to quality. Pheromone and distance are two crucial variables in ACS used to build the tour. The pheromones and distance cities collected in the first step are analyzed after a few city visits to see if both factors can be utilize to determine the quality agent's assessment. HABCO offers three different kinds of pheromone updating. The three types of updates are global, semi-global, and local. The outcomes of the experiments demonstrate that HABCO, with or without 2opt, obtains the superior solution.

Nan Zhao et al. [23] proposed a hybrid ACO–EO algorithm that expands the depth of search, which prevents local minima by combining the ACO algorithm with the Extremal Optimization (EO) local-search algorithm. Thus, by adding EO to ACO, the proposed procedure can get around ACO's drawbacks and prevent getting stuck in local optimal conditions. Simulations show that the proposed method performs more effectively than alternative ACO methods and can match the most effective multiuser detector when the ACO–EO algorithm is utilized for multiuser detection in a Direct Sequence Ultra-Wideband (DS-UWB) communication network.

HaoGao et al. [24] proposed a pair of novel updating equations for both employed and observer bees. Intelligent learning techniques are implemented to speed up the convergence rates of the onlooker, employed, and worst-employed bees. Their local and global searches are balanced by using turbulent operators. Lastly, an intelligent learning strategy is provided to quicken the convergence rate of the lowest employed bee. The designed algorithm's efficiency was determined using many benchmark functions and two industrial issues. The proposed strategy outperforms the others on both theoretical and applied problems.

C. Nandagopal et al. [25] proposed a hybrid routing system that transfers data more effectively between locations by combining the optimization of artificial bee colonies with ant colonies. The best possible routing procedure was employed to avoid congestion and loss of links. The stability of the connection and the residual energy supply influence the fitness function's design. The proposed technique is validated using fitness calculations, the update function, and solution encoding. Simulation outcomes are performed using the NS2 simulator. The results demonstrated that the hybrid algorithm was significantly more efficient than other VANET algorithms regarding the delivery of packets and latency.

Syed Mohd Faisal et al. [26] proposed an ACO-based routing technique to determine the dependability parameter value of backward and forward ants. Route discovery is made using an ACO technique, and reliable data transmission is ensured to identify novel paths, fixing broken connections in the communication networks using a reliability parameter. Forward ants search the pheromone database to get to the target node using this approach. After taking a few different routes to get to the destination node, the forward ant evaluated the packet's legitimacy and used the advanced ants' path as a guide. The backward ants compute the overall pheromone concentration and update it.

3. Proposed Algorithm

The proposed algorithm, "Dynamic Learning and Network-Distributed Exploration: advancements in Hybrid Swarm Intelligence Algorithm" is especially designed to address the difficulties in VANETs, and it marks a substantial development in hybrid swarm intelligence systems. This process adopts dynamic learning techniques and strategies for distributed network exploration that allow vehicles to change their route options instantly depending on traffic conditions and network dynamics. The network is made more robust and scalable.

Furthermore, the technique enhances communication reliability and throughput in VANETs by optimizing bandwidth use and communication parameters through dynamic resource allocation. Concerning safety-critical applications, including collision avoidance or emergency vehicle coordination. The proposed method will greatly improve network performance, safety and reliability in dynamically changing traffic conditions.

3.1. Adaptive Pheromone Update Equation with Dynamic Learning

An optimization algorithm, like ACO, can dynamically modify the rate at which pheromone levels are updated using the adaptive pheromone update with a dynamic learning rate, as shown in Equation (1).

Ant-bees, or agents as they are known, are categorized into three groups based on the ABC method: employed, onlooker, and scout bees at each level.

$$\tau_{ij}(t+1) = \big(1-\rho(t)\big).\tau_{ij}(t) + \frac{1}{N_{ant-bees}}\sum_{k=1}^{N_{ant-bees}} \Delta\tau_{ij}^{k}.\ \ \tau(t).e^{\alpha\frac{p}{|p|}}.f(i,j) \qquad (1)$$

Where,

- $(t+1)$: represents current pheromone level as of time$(t+1)$on edge(ij). Pheromone levels show which path in the optimization process is more desirable.
- $\big(1\text{-}\rho(t)\big)$: represents the rate at which pheromones decay over time is determined by this parameter. The algorithm can modify its exploration-exploitation balance in response to changes in the dynamics of the problem being addressed or the optimization process by dynamically varying.
- $\frac{1}{N_{ant-bees}}\sum_{k=1}^{N_{ant-bees}} \Delta\tau_{ij}^{k}$: represents the pheromone each individual ant-bee deposits on edge(ij) during the iteration. The total number of ant-bees in the algorithm is $(N_{ant-bees})$.
- $\tau_{ij}(t)$: represents the pheromone increment constant's current value at iteration(t). It establishes an initial quantity of pheromone that will be added in an update.
- $e^{\alpha\frac{p}{|p|}}$: This term denotes the exponential decay factor, whereαdetermines the pace at which pheromone updates lose their influence as stages advance. It assures that pheromone updates have a greater initial impact and a progressively diminishing one over time.
- p: The current phase of the tour creation process is denoted by(p). Both the strength of the pheromone update and the path creation process's progress are indicated by it.
- $|p|$: The total number of phases in the path creation process is shown by$|p|p|$. By offering a normalizing factor, it assures that the impact of pheromone changes remains constant among various problem scenarios.
- $f(i,j)$: The fitness function, denoted as $f(i,j)$, quantifies the quality of the path between nodes$(i)$and(j). It directs the optimization process by offering input on how effective various routes would be.

The optimization process in ABC optimization is divided into discrete stages to replicate the actions of ant-bees within a hive. Artificial ant-bees are initially set up to represent possible solutions, laying the groundwork for further exploration. The next responsibility for the employed ant-bees is to investigate neighbouring solutions, evaluate their quality, and adjust their placements as necessary. Onlooker ant-bees choose solutions from the data that employed bees have provided and then proceed to explore these solutions in more detail where they have potential.

Pheromone modifications at these stages would mean looking for better search options as scout ant-bees create variety in case of stagnation. Reaching solutions effectively over the solution space, ABC converges to optimal solutions by trading off exploration versus exploitation as it balances alternatively. Every phase brings some algorithm performance, and this amalgamation of all enables consistent good optimization.

Adaptive pheromone update equations with dynamic learning rates can benefit VANETs in several ways, such as increased communication efficiency and dependability. Network topology and traffic patterns might alter quickly in dynamic and unpredictably changing contexts. The algorithm can adapt its routing strategy to reduce traffic jams and fully use resources by changing the frequency at which the pheromones are updated according to the conditions of traffic on the network, which leads to a decrease in communication lag time and an increase in traffic flow when drivers in their vehicles use this dynamic routing method which leads to taking routes that are less congested at each point in time.

Moreover, the flexible adjustment of the dynamic learning rate permits the algorithm to respond to network conditions and modification of communication requirements, thereby allowing for the timely delivery of critical information while also enhancing communication reliability in VANET. Through different dynamic VANET scenarios, the algorithm remains effective because it responds to the network dynamics, thus improving resilience and increasing control.

Altogether, the adaptive pheromone updating equation with dynamic learning rate emerges as an effective solution to the specific problems encountered in VANET communication, improving vehicular communication networks' global efficiencies and reliabilities. Based on the quality of the solutions discovered, this algorithm iteratively modifies the pheromone levels on each edge of the solution path built by individual ant-bee. The method keeps running until it reaches a high-quality solution after a predetermined number of iterations. The ultimate pheromone levels are output after the predetermined number of iterations, as shown in algorithm 1.

Algorithm-1: Adaptive pheromone update algorithm with dynamic learning rate
1. Initial pheromone levels (τ) 2. Number of iterations (max_iter) 3. Number of ant-bees ($N_{ant-bees}$) 4. Problem-specific parameters and constraints 5. Initialize pheromone levels (τ) with random values - for t = 1 to max_iter do - for each bee k = 1 to $N_{ant-bees}$ do - Constructing solution path using ant-like behavior • Evaluate solution quality • Update pheromone levels on edges based on solution quality and path - for each edge (i, j) in the solution path do $\tau_{ij}(t+1) = \left(1-\rho(t)\right).\tau_{ij}(t) + \frac{1}{N_{ant-bees}} \sum_{k=1}^{N_{ant-bees}} \Delta\tau_{ij}^{k}.\ \tau(t).e^{\alpha\frac{p}{\lvert p \rvert}}.f(i,j)$ 6. Output final Pheromone levels (r)

3.2. Collective Exploration with Network-Distribution Pheromone Update

A crucial method in optimization algorithms, collective exploration with network-distributed pheromone update, is especially motivated by ant colony behavior, as shown in Equation (2).

$$\tau_{ij}(t+1) = \left(1-\rho(t)\right).\tau_{ij}(t) + \frac{1}{N_{neighbors}} \sum_{j\in neighbors(i)} \Delta\tau_{ij}^{k}\ .\left(1+\frac{(\gamma(t))}{1+e^{-\sigma(t)}}\right) \tag{2}$$

Where:

- $\tau_{ij}(t+1)$: represents the pheromone level at time (t+1) on the edge (ij). Once the pheromone update process is complete, the term denotes the updated pheromone level on the edge.
- ρ: represents the constant rate of pheromone evaporation. It establishes the rate at which pheromones on edges evaporate throughout the network globally. This parameter influences the rate at which pheromone levels decrease over time.
- $\frac{1}{N_{neighbors}} \sum_{j\in neighbors(i)} \Delta\tau_{ij}^{k}\ .\left(1+\frac{(\gamma(t))}{1+e^{-\sigma(t)}}\right)$ represents the quantity of pheromone that each nearby ant-bee adds to the edge(ij). $N_{neighbors}$indicates the quantity of adjacent nodes within the network that exchange information. The time-varying parameter $\gamma(t)$regulates the impact of pheromone updates from nearby ant-bees. According to time-varying dynamics, it modifies the updated contribution of neighboring ant-bees. A time-varying parameter called $\sigma(t)$regulates the logistic sigmoid function's form. It modifies the logistic curve's steepness and structure, which affects how information from nearby ant-bees is integrated.

This method involves artificial agents communicating with their surrounding agents, such as ant bees, to share knowledge about potential solutions. Through decentralized communication, the swarm may more effectively explore the solution space [27]. Depending on the solutions' quality, each agent modifies the pheromone levels on solution components and notifies nearby agents of these adjustments.

This allows the swarm to use its collective intelligence, and the technique can steer the search process towards regions within the solution space that are most likely to contain good solutions. As a result of the continuous interaction of agents, network-distributed pheromones enhance the adaptability of the algorithm to dynamic circumstances. Therefore, this permits rapid adjustment by swarms in response to alterations in the attributes of the problem around it. Collective exploration with network-distributed pheromone updating allows for effective information sharing and agent collaboration. By enhancing exploration and exploitation within optimization algorithms, this approach can leverage these abilities. Collective exploration with network-distributed pheromone updating can greatly improve performance in VANETs, where V2V communication is essential for efficiency and safety.

Vehicles can exchange information about traffic conditions, road hazards, and ideal routes through network-distributed pheromone updates by applying ACO ideas to VANETs. Due to the decentralized communication among them, vehicles can collaboratively explore and exploit the dynamic environment, thus facilitating route selection and congestion management.

Moreover, reliable and effective communication is ensured by the adaptability of the algorithm to changing traffic patterns and road conditions, leading to enhanced delivery of packets, lowered end-to-end delays, and increased throughput in VANETs. Pheromone levels are first initialized by algorithm 2, and then it uses collaborative exploration to iteratively construct solution pathways. According to pheromone levels, each artificial bee chooses nearby components probabilistically, updates the solution path and evaluates its quality.

Then, the quality of solutions found influences how much pheromone levels are adjusted. Ant-bees help in spreading the pheromone update to other ant-bees through the network. They pass on information about how good the solution is and what has been done with the pheromone to ant-bees nearby. This method is appropriate for VANETs because it adopts collective exploration and communication in this procedure to efficiently explore the feasible solution field and converge towards some quality solutions.

Algorithm-2: Collective exploration with network-distributed pheromone update
1. Initial pheromone levels (τ) 2. Number of iterations (max_iter) 3. Number of ant-bees ($N_{ant-bees}$) 4. Number of neighbors ($N_{neighbors}$) 5. Problem-specific parameters and constraints 6. Initialize pheromone levels (τ) with random values or a predefined heuristic - for t = 1 to max_iter do - for each bee k = 1 to $N_{ant-bees}$ do - Construct a solution path using collective exploration - for each component i in the solution, do 7. Calculate the probability of selecting each neighboring component j 8. Evaluate solution quality 9. Update pheromone levels on edges based on solution quality - for each edge (i, j) in the solution path do $\tau_{ij}(t+1) = (1-\rho(t)).\tau_{ij}(t) + \frac{1}{N_{neighbors}} \sum_{j \in neighbors(i)} \Delta\tau_{ij}^{k}$ 10. Exchange information with neighbors - for each bee k = 1 to $N_{ant-bees}$ do - Share solution quality and pheromone updates with neighbors 11. Update pheromone levels based on information received from neighbors - for each edge (i, j) in the network do $\tau_{ij}(t+1) = (1-\rho(t)).\tau_{ij}(t) + \frac{1}{N_{neighbors}} \sum_{j \in neighbors(i)} \Delta\tau_{ij}^{k} .\left(1 + \frac{(\gamma(t))}{1+e^{-\sigma(t)}}\right)$

3.3. Adaptive Exploration-Exploitation Trade0off with Reinforcement Learning

For optimization algorithms to dynamically balance between exploring novel solution regions and exploiting existing good solutions based on input from the environment or prior experiences, the adaptive exploration-exploitation trade-off with reinforcement learning is a key mechanism shown in Equation (3).

$$P_{ij} = \frac{\tau_{ij}^{\alpha}.Q_{ij}^{\beta}.\left(\frac{\tau max - \tau_{ij}}{\sum_{k=1}^{m} \tau max - \tau_k}\right)}{\sum_{k \epsilon allowedmoves} \tau_{ij}^{\alpha}.Q_{ij}^{\beta}\left(\frac{\tau max - \tau_{ij}}{\sum_{k=1}^{m} \tau max - \tau_k}\right)} . \left(1 + \zeta(t). \frac{1}{1+e^{-\chi(t)}}\right) \quad (3)$$

Where,

- P_{ij}: represents the probability of choosing edge (ij) in the process of building a solution. It shows the probability of selecting a specific solution element (edge) according to its features.
- τ_{ij}: represents on-edge pheromone level(ij). Pheromone levels in optimization techniques, such as ACO, indicate the acceptability or attractiveness of solution components. Higher pheromone levels usually indicate better solutions.
- Q_{ij}: represents Q-value connected to edge(ij) in a framework for reinforcement learning. The projected long-term benefit or utility of choosing edge(ij) based on prior knowledge and experiences is represented by the Q-value. More promising solutions are usually indicated by higher Q-values.
- α and β: The pheromone effect is controlled by the parametersα,βand Q-values, respectively, enabling adaptive modification according to the advancement of learning.
- τ_{max} : Maximum observed pheromone across all edges.
- τ_k : Usually, k is utilized as an index variable to represent every single agent.
- m : Total number of agent ant-bees.
- $\sum_{k \epsilon allowedmoves} \tau_{ij}^{\alpha}. Q_{ij}^{\beta}$: represents the summation term that reflects the overall impact of Q-values and pheromone levels for all permitted edges. It guarantees a

legitimate probability distribution by adding the probabilities computed for each possible move.

- $\left(1+\zeta(t)\right).\frac{1}{1+e^{-\chi(t)}}$: presents a reinforcement learning-based dynamic modification to the exploration-exploitation trade-off. The time-varying parameter $\zeta(t)$ regulates the adjustment's magnitude. The form of the logistic sigmoid function, which modifies the exploration-exploitation balance over time, is controlled by a time-varying parameter called $\chi(t)$.

This approach adaptively changes the exploration and exploitation strategies to ensure that the algorithm explores new solution spaces under high uncertainty and exploits the well-known promising solutions under high confidence. The algorithm uses reinforcement learning techniques for estimating the expected rewards based on different actions through past interactions with the environment. This allows the system to make informed decisions that effectively maximize long-term performance.

Within VANETs, where communication between vehicles is critical to both efficiency and safety, routing and resource allocation decisions are optimized using the adaptive exploration-exploitation trade-off with reinforcement learning equation. The algorithm is constantly balancing exploration and exploitation to adjust to the dynamic and unpredictable characteristics of VANETs during low-traffic or high-reliability periods, and it might control known routes or channels for communication to optimize performance.

Ant-bees utilize the adaptive exploration-exploitation trade-off equation to determine the probability P_{ij} for every edge. Ant-bees use this probability to choose which edge is most likely to be exploited or explore a random edge, as shown in algorithm 3.

Algorithm-3: Adaptive Exploration-Exploitation Trade-off with Reinforcement Learning

1. Set parameters: α, β, $\zeta(t), and \chi(t)$
2. Initialize Q-values Q (ij) for all edges.
3. Set convergence criteria.
4. for each bee:
   - Calculate the probability P_{ij} for each edge (ij) using the equation

$$P_{ij} = \frac{\tau_{ij}^{\alpha}.Q_{ij}^{\beta}.\left(\frac{\tau max-\tau_{ij}}{\sum_{k=1}^{m}\tau max-\tau_k}\right)}{\sum_{k\epsilon allowedmoves}\tau_{ij}^{\alpha}.Q_{ij}^{\beta}\left(\frac{\tau max-\tau_{ij}}{\sum_{k=1}^{m}\tau max-\tau_k}\right)}.\left(1+\zeta(t).\frac{1}{1+e^{-\chi(t)}}\right)$$

   - With probability ϵ, select a random edge to explore. Otherwise, select the edge with the highest probability for exploitation.
5. For each selected edge: Update Q-values
6. Adjust parameters:
   - Update time-varying parameters $\zeta(t), and \chi(t)$ as needed.
7. Check convergence:
   - If convergence criteria are met, stop; otherwise, continue.

The algorithm for adaptive exploration-exploitation trade-off using reinforcement learning is shown in Figure 1. Initialization is the first step, during which parameters are set. The method then goes into a loop that doesn't stop until the convergence requirements are satisfied. In this loop, Ant-bees depend on the equation given to measure how likely each edge is and use it as a guide in determining whether to explore or exploit. They proceed by taking the chosen action and observing the reward before updating Q-values using the Q-learning rule. The loop may continue running depending on the convergence criteria, while parameters are altered if needed.

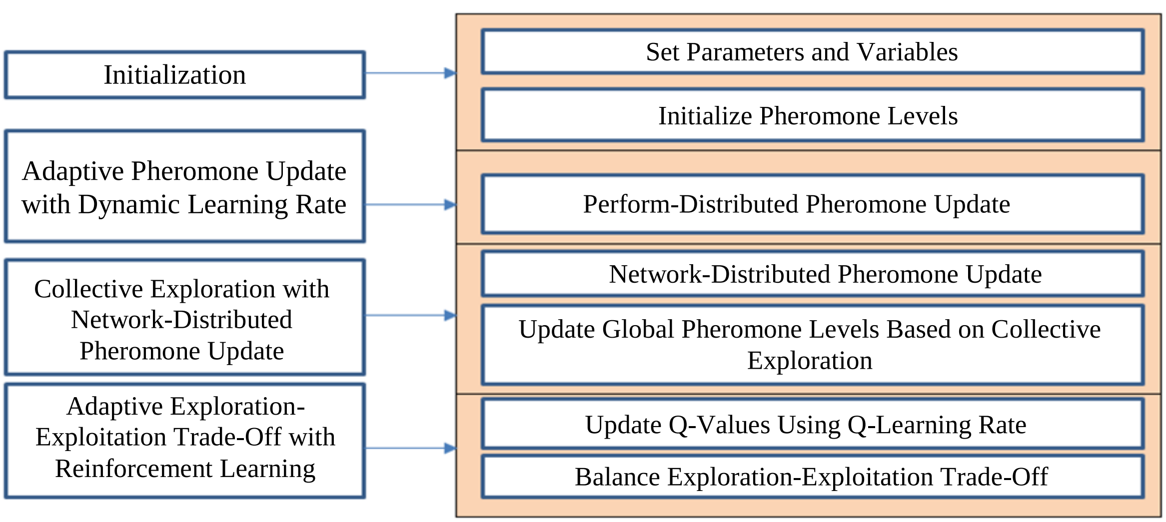

Fig. 1 HSIA block diagram

4. Simulation Results

In this work, MATLAB is utilized to simulate the results of the proposed approach. These include the total number of vehicles, their velocity, and the size of the packets to evaluate the suggested adaptive pheromone updates with Dynamic Learning, Collective Exploration with Network-Distributed Pheromone Update and Adaptive Exploration-Exploitation Trade-off with Reinforcement Learning. Simulation is used to process data.

A total of 300 vehicles were taken into consideration during the simulation phase, and the speed limit that was taken into consideration is 60 to 120 km/h; ten simulation runs with a 100-second simulation time, and a 1024-byte size of packet is employed for the simulation. The implemented strategy is compared with ABC and ACO. Three metrics are examined for performance exploration: throughput, packet delivery ratio, and end-to-end delay.

4.1. Packet Delivery Ratio (PDR)

By using an HSIA to dynamically optimize node placements, PDR in VANETs is enhanced. Equation (4) is used to compute PDR. This adaptive technique finds an equilibrium between exploration and exploitation to transport packets optimally. It also offers effective path optimization search [29]. As indicated in Table 1, PDR is computed by comparing the total number of packets transmitted from the sender to the destination and the total number of packets that arrived at the receiver's end. Figure 2 illustrates how much better the PDR in this proposed HSIA is contrasted with the traditional ACO and ABC. The HSIA's average PDR is 37.1%, but the average PDR of ABC and ACO are 32% and 36.7%, respectively. Accordingly, HSIA's average PDR is 1.09 % higher than ACO's and 15.94 % higher than ABC's.

$$Packet\ delivery\ ratio = \frac{Number\ of\ packets\ successfully\ delivered\ by\ HSIA}{Total\ number\ of\ packets\ sent} * 100 \quad (4)$$

Table 1. PDR according to speed

Speed	Improvement of Proposed HSIA over ACO and ABC		
	Packet Delivery Ratio (%)		
	ACO	ABC	HSIA
20	0.25	0.24	0.27
40	0.29	0.26	0.28
60	0.31	0.31	0.3
80	0.42	0.36	0.43
100	0.44	0.43	0.44
120	0.48	0.44	0.49

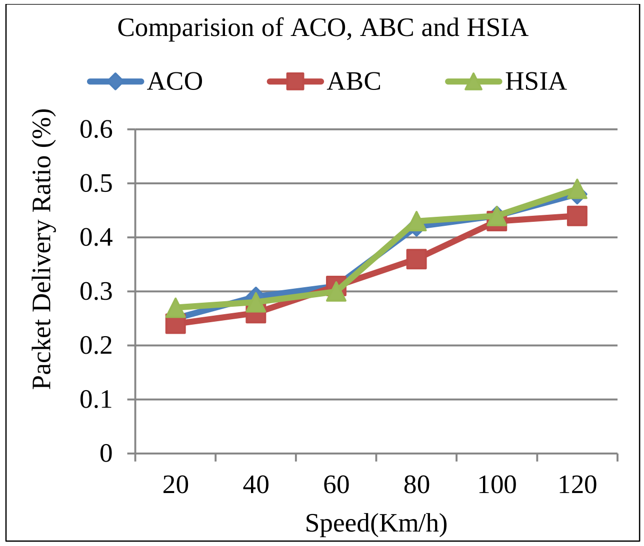

Fig. 2 Packet delivery ratio

4.2. End-to-End Delay (EED)

An HSIA algorithm is used to minimize EED in VANETs. Equation (5) is used to calculate EED. This dynamic node position optimization encourages efficient communication pathways in dynamic vehicle situations, reducing delays and enhancing overall performance. As demonstrated in Table 2, HSIA outperforms the ABC and ACO methods in terms of sending data with the least amount of delay from source to recipient utilizing the time of packets.

Soon, the neighbor's location will be anticipated. ABC's EED is 32.6667 milliseconds on average, ACO has an average EED of 28.63333 milliseconds, and HSIA has an average EED of 27.03333 milliseconds. This discrepancy shows that HSIA's EED was reduced by 5.59% compared to ACO and 17.25% compared to ABC, as shown in Figure 3.

$$End - to - End\ dealy = Transmission\ delay + Propogation\ delay + Queing\ delay \quad (5)$$

Table 2. EED according to traffic density

Vehicle density	Improvement of proposed HSIA over ACO and ABC		
	End-to-End delay (milliseconds)		
	ACO	ABC	HSIA
50	26	29	25
100	27	31	26
150	28	32	25
200	29	35	27
250	31	36	30
300	36	39	33

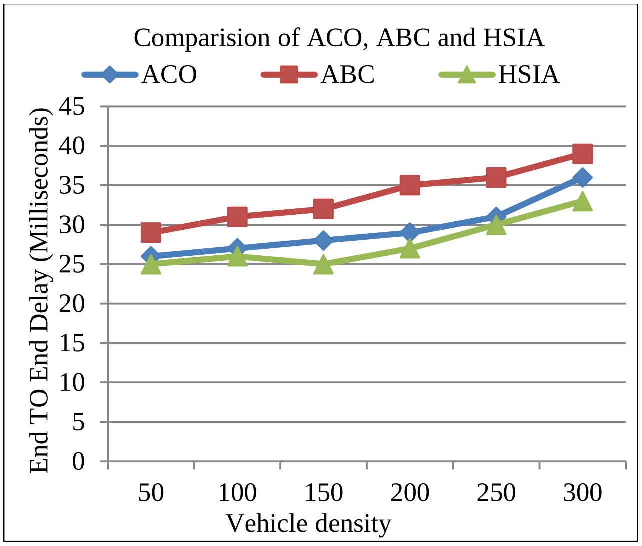

Fig. 3 End-to-End delay

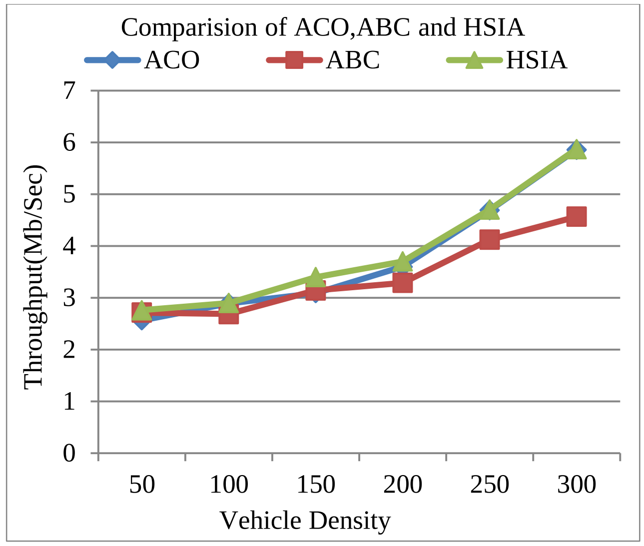

Fig. 4 Throughput

4.3. Throughput

HSIA increases throughput in VANETs. Equation (6) is used to calculate throughput. This is accomplished as indicated in Table 3, which shows how node placements are dynamically optimized, efficient communication paths are encouraged. Delays are decreased to boost network throughput overall in dynamic vehicle situations [2].

This adaptive method efficiently searches for the best pathways while balancing optimal throughput. Throughput is the amount of data that can flow in a predetermined amount of time. Figure 4 illustrates how the proposed approach HSIA significantly improves overall throughput performance when compared to the current ABC and ACO approaches. ABC, ACO, and HSIA have the following average throughputs: 3.26441 Mb/sec, 3.5345 Mb/sec, and 3.5868 Mb/sec, respectively. This discrepancy suggests that HSIA's throughput increased by 9.87% over ABC and 1.48% over ACO.

$$Throughput = \frac{Number\ of\ packets\ successfully\ routed\ by\ HSIA}{Total\ time\ taken\ to\ route\ the\ packets} \quad (6)$$

Table 3. Throughput according to traffic density

Vehicle Density	Improvement of proposed HSIA over ACO and ABC		
	Throughput (mb/sec)		
	ACO	ABC	HSIA
50	2.567	2.7132	2.76
100	2.889	2.6859	2.9
150	3.089	3.1416	3.4
200	3.6	3.289	3.7
250	4.689	4.1208	4.7
300	5.86	4.5654	5.87

PDR, EED, and throughput are the three overall performance metrics employed in this work and are crucial for assessing the dependability and efficacy of communication protocols in VANETs. When examining the performance measurements of ABC, ACO, and HSIA, significant information regarding the impact of congestion on network performance is shown. When comparing HSIA to ABC and ACO, Table 4 shows the observed increases in PDR, throughput, and reduced EED, highlighting the effectiveness of congestion management solutions. Figure 5 displays the average PDR, EED, and throughput values. These enhancements make the VANET more dependable and efficient, ensuring seamless communication between vehicles and infrastructure elements even in challenging and congested conditions.

Table 4. Improvement of parameters according to traffic density

Improvement of proposed HSIA over ACO and ABC			
Traffic Density	Average PDR		
	ACO	ABC	HSIA
300	36.7 %	32%	37.1%
	Average EED		
	ACO	ABC	HSIA
	28.63333 Milliseconds	32.6667 Milliseconds	27.03333 milliseconds
	Average Throughput		
	ACO	ABC	HSIA
	3.5345 mb/sec	3.26441 mb/sec	3.5868 mb/sec

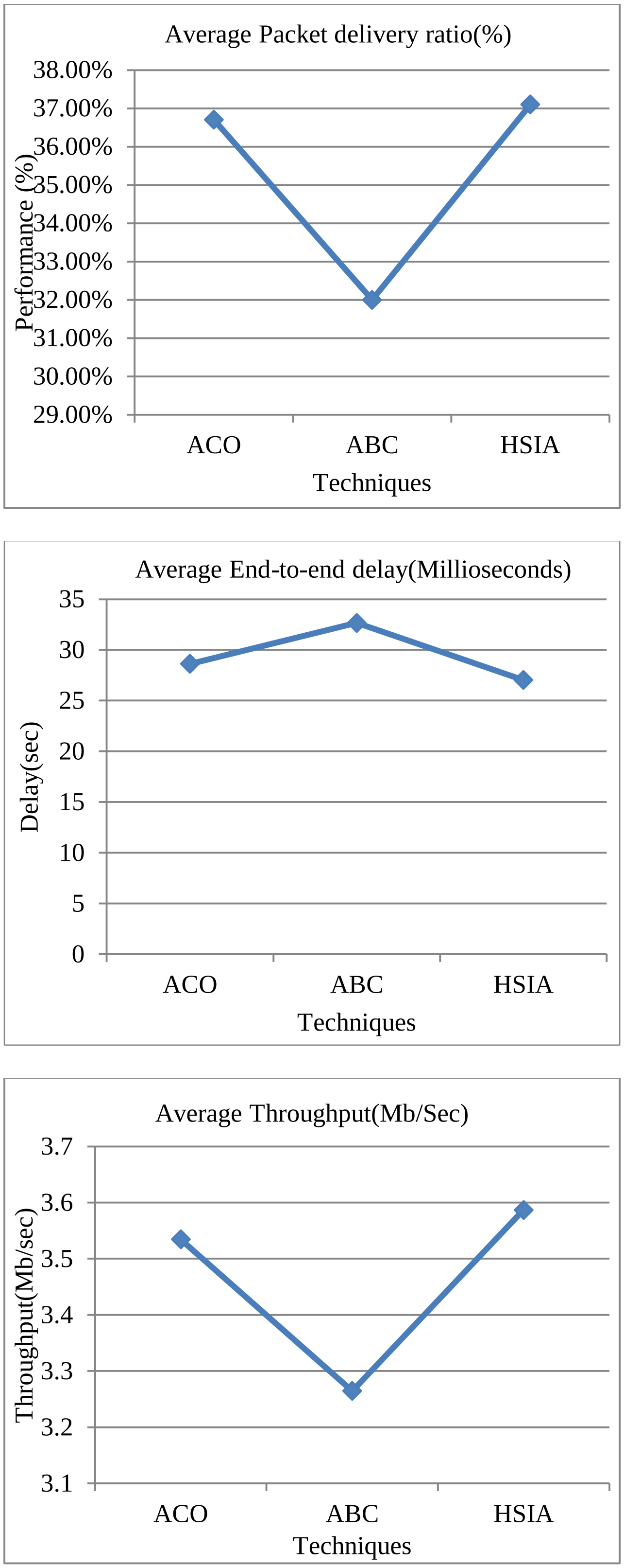

Fig. 5 Average PDR, EED and Throughput

5. Conclusion

Within hybrid swarm intelligence mechanisms, it is very significant that the optimization algorithms are enriched by network-distributed exploration and dynamic learning.

By merging adaptive pheromone update equations with dynamic learning rates, network-distributed pheromone updates with collective exploration and reinforcement learning with adaptive exploration-exploitation trade-offs, we can use both ABC optimization and ACO. This hybrid technique enhances the algorithm's robustness, adaptability, and efficacy in addressing complex problems.

The results of the PDR demonstrate the superiority of HSIA, which surpassed both ACO of 36.7% and ABC of 32% with a PDR of 37.1%. In dynamic VANET setups, utilizing HSIA as the main optimization method and augmenting it with ABC and ACO guarantees efficient congestion mitigation and dependable packet delivery.

The average EED values largely determine the effectiveness of congestion control in VANETs. With an average latency of 27.03333 milliseconds, HSIA outperforms both ACO of 28.63333 milliseconds and ABC of 32.6667 milliseconds.

In dynamic VANET setups, utilizing HSIA as the main optimization technique and complementing it with ABC and ACO ensures effective congestion mitigation and timely packet delivery. VANETs' efficiency in controlling congestion can be understood from the average throughput values.

With a throughput of 3.5868 Mb/sec, HSIA exceeds ABC of 3.26441 Mb/sec and ACO of 3.5345 Mb/sec, demonstrating its efficacy in sustaining high data transmission rates for congestion reduction in scenarios that are both mobile and decentralized like VANETs. These improvements are vital because they increase the PDR, lower EED and increase throughput.

Proposed algorithms are more effective than traditional solutions when it comes to performance improvement and can be used efficiently to solve various optimization issues. In future research, it would be important to explore new dynamic ways of learning, like how one can combine machine learning strategies for adjusting parameters adaptively from real-time traffic information. In addition, improving network communication protocols may enable a more reliable and efficient network-centric exploration process that enhances the resilience and adaptability of mixed models of swarm intelligence algorithms under changing VANET conditions.

References

[1] Farhan Aadil et al., "CACONET: Ant Colony Optimization (ACO) Based Clustering Algorithm for VANET," *PloS One*, vol. 11, no. 5, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[2] M. Sri Lakshmi et al., "Minimizing the Localization Error in Wireless Sensor Networks Using Multi-Objective Optimization Techniques," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 10, no. 2s, pp. 306-312, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Vinita Jindal, and Punam Bedi, "An Improved Hybrid Ant Particle Optimization (IHAPO) Algorithm for Reducing Travel Time in VANETs," *Applied Soft Computing*, vol. 64, pp. 526-535, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[4] Vijay Walunj, Diego Marcilio, and Bhaveet Nagaria, "Dynamic Congestion Control Mechanisms for Enhanced Efficiency in Vehicular Ad-Hoc Networks," *International Journal of Computer Engineering in Research Trends*, vol. 11, no. 5, pp. 24-32, 2024. [Publisher Link]

[5] Muhammad Arif et al., "Optimization of Communication in VANETs Using Fuzzy Logic and Artificial Bee Colony," *Journal of Intelligent & Fuzzy Systems*, vol. 38, no. 5, pp. 6145-6157, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] Prashant G. Tandale, "VANET: Application of Mobile Communications in Road Traffic," *Proceedings of the 4th National Conference; INDIACom-2010: Computing for Nation Development*, pp. 1-5, 2010. [Google Scholar] [Publisher Link]

[7] G. Ravikumar et al., "Cloud Host Selection Using Iterative Particle-Swarm Optimization for Dynamic Container Consolidation," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 10, no. 1s, pp. 247-253, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Kamlesh Rana, Sachin Tripathi, and Ram Shringar Raw, "VANET: Expected Delay Analysis for Location Aided Routing (LAR) Protocol," *BVICAM's International Journal of Information Technology*, vol. 8, no. 2, pp. 1029-1037, 2016. [Google Scholar] [Publisher Link]

[9] M. Kayalvizhi, and S. Geetha, "Efficacy Artificial Bee Colony Optimization-Based Gaussian AOMDV (EABCO-GAOMDV) Routing Protocol for Seamless Traffic Rerouting in Stochastic Vehicular Ad Hoc Network," *International Journal of Computer Networks and Applications*, vol. 10, no. 6, pp. 993-1014, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Murad Khan, Ibrahim Shayea, and Joel J.P.C. Rodrigues, "Adaptive Hybrid Routing for Vehicular Ad-Hoc Networks Using Swarm Intelligence and Neural Network-Based Traffic Prediction," *International Journal of Computer Engineering in Research Trends*, vol. 11, no. 7, pp. 13-23, 2024. [Publisher Link]

[11] Dervis Karaboga, "*An Idea Based on Honeybee Swarm for Numerical Optimization*," Technical Report-TR06, Erciyes University, Engineering Faculty, Computer Engineering Department, 2005. [Google Scholar] [Publisher Link]

[12] E.V.N. Jyothi et al., "A Graph Neural Network-Based Traffic Flow Prediction System with Enhanced Accuracy and Urban Efficiency," *Journal of Electrical Systems*, vol. 19, no. 4, pp. 336-349, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] V.S. Saranya et al., "Real-Time Traffic Flow Optimization Using Adaptive IoT and Data Analytics: A Novel DeepStreamNet Model," *2024 4th International Conference on Sustainable Expert Systems (ICSES)*, Kaski, Nepal, pp. 312-320, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] K.R. Ramkumar, K. Sakthivel, and C.S. Ravichandran, "ACBRAAM: A Content Based Routing Algorithm Using Ant Agents for MANETs," *BIJIT-BVICAM's International Journal of Information Technology*, vol. 3, no. 1, pp. 276-280, 2011. [Google Scholar] [Publisher Link]

[15] Sadashiv Shirabur, Shivaling Hunagund, and Suresh Murgd, "VANET Based Embedded Traffic Control System," *2020 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT)*, Bangalore, India, pp. 189-192, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[16] C. Kumuthini et al., "Ant with Artificial Bee Colony Techniques in Vehicular Ad-hoc Networks," *International Journal of Data Informatics and Intelligent Computing*, vol. 2, no. 3, pp. 21-28, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Ning Guo et al., "A Hybrid Ant Colony Optimization Algorithm for Multi-Compartment Vehicle Routing Problem," *Complexity*, vol. 2020, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[18] Sengathir Janakiraman, "A Hybrid Ant Colony and Artificial Bee Colony Optimization Algorithm-Based Cluster Head Selection for IoT," *Procedia Computer Science*, vol. 143, pp. 360-366, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[19] Anxiang Ma et al., "An Adaptive Hybrid Ant Colony Optimization Algorithm for the Classification Problem," *Information Technology and Control*, vol. 48, no. 4, pp. 590-601, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[20] M. Kefayat, A. Lashkar Ara, and S.A. Nabavi Niaki, "A Hybrid of Ant Colony Optimization and Artificial Bee Colony Algorithm for Probabilistic Optimal Placement and Sizing of Distributed Energy Resources," *Energy Conversion and Management*, vol. 92, pp. 149-161, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[21] Changsheng Zhang, and Bin Zhang, "A Hybrid Artificial Bee Colony Algorithm for the Service Selection Problem," *Discrete Dynamics in Nature and Society*, vol. 2014, no. 1, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[22] Abba Suganda Girsang, Chun-Wei Tsai, and Chu-Sing Yang, "A Hybrid Ant-Bee Colony Optimization for Solving Traveling Salesman Problem with Competitive Agents," *Mobile, Ubiquitous, and Intelligent Computing*, pp. 643-648, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[23] Nan Zhao, Xianwang Lv, and Zhilu Wu, "A Hybrid Ant Colony Optimization Algorithm for Optimal Multiuser Detection in DS-UWB System," *Expert Systems with Applications*, vol. 39, no. 5, pp. 5279-5285, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[24] Hao Gao et al., "An Improved Artificial Bee Colony Algorithm with its Application," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 1853-1865, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[25] C. Nandagopal et al., "Mobility Aware Zone-Based Routing in Vehicle Ad hoc Networks Using Hybrid Metaheuristic Algorithm," *Intelligent Automation & Soft Computing*, vol. 36, no. 1, pp. 113-126, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Syed Mohd Faisal, and Taskeen Zaidi, "Implementation of ACO in VANETs with Detection of Faulty Node," *Indian Journal of Science and Technology*, vol. 14, no. 19, pp. 1598-1614, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[27] Fuhui Zhou, Thomas Lagkas, and Farhan Aadil, "Optimizing Edge Computing for Internet of Drones: A Hybrid Approach Using Deep Learning and Swarm-Based Routing," *Macaw International Journal of Advanced Research in Computer Science and Engineering*, vol. 10, no. 1, pp. 64-73, 2024. [Google Scholar] [Publisher Link]

[28] Omar Sami Oubbati, Adnan Shahid Khan, and Madhusanka Liyanage, "Blockchain-Enhanced Secure Routing in FANETs: Integrating ABC Algorithms and Neural Networks for Attack Mitigation," *Synthesis: A Multidisciplinary Research Journal*, vol. 2, no. 2, pp. 1-11, 2024. [Google Scholar] [Publisher Link]

[29] P. Suman Prakash et al., "Mixed Linear Programming for Charging Vehicle Scheduling in Large-Scale Rechargeable WSNs," *Journal of Sensors*, vol. 2022, no. 1, 2022. [CrossRef] [Google Scholar] [Publisher Link]