SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V11I7P103

Volume 11 Issue 7, 20-36, July 2024

Original Article

Enhanced Artificial Bee Colony Algorithm with Adaptive Position Update and Adaptive Exploration: Exploiting Optimization for Congestion Control in Vehicular Ad-Hoc Networks

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Received: 02 May 2024 Revised: 03 June 2024 Accepted: 02 July 2024 Published: 27 July 2024

Abstract - *A subset of Mobile Ad-hoc Networks (MANETs) consisting of Roadside Units (RSUs) and vehicles as wireless nodes are called Vehicular Ad-hoc Networks (VANETs). The basic idea is to allow vehicles to communicate among themselves about the movement of vehicles and operations, such as speed, location, acceleration, and deceleration, to roadside units. RSUs are placed along the roadside and are used by vehicles to communicate with one another. Every new vehicle has an On-Board Unit (OBU) installed. Communication between vehicles and between vehicles and infrastructure is crucial for several reasons, including public safety, passenger comfort, and road safety. A well-known method of artificial bee colony is the evolutionary algorithm having good performance in exploration although not in exploitation. This paper presents an Enhanced Artificial Bee Colony Algorithm with Adaptive Position Update and Adaptive Exploration-Exploiting (EABC-APUAEE), a novel strategy that improves the performance of the Artificial Bee Colony (ABC) algorithm. This combines two crucial adaptive mechanisms: the Adaptive Position Update (APU) and the Adaptive Exploration-Exploiting (AEE) optimization. The APU modifies bee locations to make the solution converge more quickly, while AEE optimization manages to maintain both exploration and exploitation. According to simulation results, the method which is proposed outperforms the original artificial bee colony algorithm by means of high packet delivery ratio, throughput, and decreased end-to-end delay. The simulation findings show that an enhanced artificial bee colony method with adaptive strategies can attain optimal routes more successfully. The performance is analyzed using MATLAB. The packet delivery ratio and throughput of EABC-APUAEE showed a significant increase to 30.78% and 37.21% when compared to ABC. In comparison to ABC end-to-end delay of EABC-APUAEE decreased to 50.54%.*

Keywords - *Vehicular ad-hoc networks, Adaptive mechanism, Artificial bee colony, Roadside unit, Onboard unit.*

1. Introduction

In the years come, VANETs are expected to play a major part in improving traffic efficiency, road security and safety in transportation systems [1]. Decrease in congestion and efficiency in transportation systems is increased with the help of the Intelligent Transport System (ITS). VANETs are key elements in the design of ITS. Vehicles having wireless communication devices, such as onboard units and sensors are part of these networks. OBU alerts the driver about potential danger [2].

A VANET is created when the vehicle connects with the components of network infrastructure [3-6]. Consistent information flow between infrastructural nodes and vehicles is made easier by VANETs. Under this scenario, vehicles would turn into extremely useful mobile sensors that communicate with infrastructure components such as RSUs, which are placed throughout the road network to gather traffic data. Furthermore, the consistent transmission of data between vehicles, such as location and speed, proves to be an extremely effective means for every vehicle to track its local traffic conditions independently.

The main aim of VANET architecture is to enable communication between vehicles which are mounted with OBU and stationary roadside devices such as RSU [7, 8]. Vehicle-to-Vehicle (V2V) communication networks can be primarily used for safety and security that enable continuous communication between vehicles without relying on static infrastructure for support shown in Figure 1. Vehicle-to-Infrastructure (V2I) communication networks facilitate vehicles and roadside units to communicate, mostly for collecting data, as shown in Figure 2.

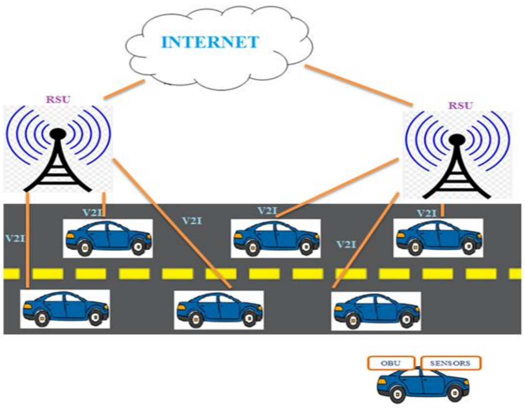

Fig. 1 V2Vcommunication network

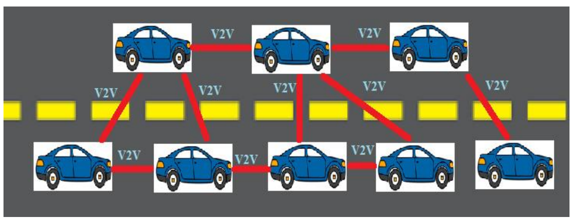

Fig. 2 V2I communication network

Karaboga of Erciyes University in Turkey introduced ABC, a novel swarm intelligence algorithm, in 2005. This algorithm's efficacy was evaluated in 2007. The algorithm was motivated by the intelligence-searching behaviors of bees [9, 10]. Three different kinds of artificial bees are used. They are employed bees, onlooker bees, and scout bees. An employed bee searches the search region for solutions, while an onlooker bee chooses its search path based on the information provided by an employed bee. Scout bee actively seeks out alternatives to optimize the overall performance of the hive [11]. The searching function of ABC works well, but it has limited potential for exploitation. A population-based optimization algorithm needs to balance exploration and exploitation carefully [12]. Within the ABC algorithms, search space exploitation is the responsibility of employed and onlooker bees, whereas the scout bees are responsible for exploration. Neighboring solutions related to each food source are selected at random during the employed and onlooker bee stages. Consequently, there is no assurance that these solutions will be better than the preceding ones.

ABC algorithm has gained popularity in the field of optimization algorithms due to its inspiration from honey bee foraging behavior [13]. However, this work proposed an enhanced ABC algorithm to address the inherent problems of convergence speed and solution quality. The integration of adaptive position update and adaptive exploration-exploitation optimization is an important advancement in the field of optimization algorithms, especially when it comes to handling different problems like congestion control. Adaptability is highly important in dynamic contexts like vehicular Ad-hoc networks, where traffic conditions change quickly. The adaptive position update algorithm incorporates a dynamic technique for adjusting the locations of artificial bees in order to provide real-time responsiveness to changing traffic patterns. Furthermore, adaptive exploration-exploitation optimization enhances the algorithm by cleverly balancing the exploration of novel solution spaces with the exploitation of identified potential regions. These adaptive techniques show tremendous potential for enhancing VANET performance by offering an unpredictable and intelligent strategy for controlling congestion under dynamic and erratic traffic situations.

The difficulties and problems associated with the ABC optimization algorithms employed, Onlooker, and Scout Bee stages are closely related to how VANETs use them to manage congestion. Improving solution quality is the primary difficulty during the employed bee stage because poor strategies might lead to less-than-ideal results; hence, an effective mechanism is required to raise the standard of solutions. Additionally, it is critical to strike the right equilibrium between exploration and exploitation because, in the dynamic environment of VANETs, an overemphasis on exploitation might result in less-than-ideal solutions. Another major obstacle is that ABC and related optimization algorithms are prone to being trapped in local optima, which seems better in a particular environment but not globally.

Because it might be challenging to determine which solutions are worthy of additional examination, choosing the most promising solutions and effectively assigning Onlooker bees present significant obstacles during the onlooker bee stage. Inadequate communication could compromise the algorithm's overall effectiveness. Good communication and information sharing between onlookers and employed bees are essential. Stagnation is a phenomenon that can lead to less-than-ideal outcomes and impede the onlooker bee's capacity. The quick recognition and abandonment of substandard ideas, together with the restarting of the search, are significant obstacles in the Scout bee stage. In order to prevent early convergence to less-than-ideal solutions and to guarantee the investigation of a variety of search regions, scout bees are vital to the preservation of population diversity.

The complex issue of ensuring that the abandonment mechanism encourages exploration across multiple regions instead of concentrating on a particular subset directly affects the exploratory capacity of the algorithm. The EABC-APUAEE optimization algorithm is developed in response to the need to overcome significant obstacles in rapidly changing circumstances and unpredictable environments, particularly in the context of VANETs. Multiple key elements drove the optimization of the algorithm. The most important of these is the requirement for real-time traffic management in progressively more intricate urban traffic scenarios, which emphasizes the goal of the algorithm to provide prompt, flexible solutions to reduce traffic jams, improve traffic flow, and minimize delays. Artificial bees must adapt to the optimization environment in order to navigate sudden changes in traffic conditions, which informs the algorithm's adaptive position update mechanism. This flexibility guarantees that real-time information is used to optimize solutions. In order to optimize decision-making in quickly changing environments, the algorithm also presents a flexible exploration and exploitation strategy. This strategy aims to create a dynamic equilibrium in response to the dynamics of optimization challenges as they evolve.

The key contributions of this paper are defined as follows:

- The study presents an improved algorithm for optimizing artificial bee colonies, which considerably improves congestion control in VANETs.
- The algorithm outlines how to optimize limited network resources, such as bandwidth and connectivity between vehicles, significantly increasing the effectiveness of congestion management.
- By strategically allocating resources, it effectively reduces delays and traffic congestion, enabling more dynamic vehicular flow within the network.
- In addition, the proposed algorithm gives the network's decision-making process flexibility, allowing for quick adjustments in response to changing traffic patterns and unforeseen road circumstances.
- This algorithm's ability to control congestion in real-time is one of its key features it is important to note that in VANET environments, where timely response is necessary to maintain operational efficiency and traffic safety, prompt response is crucial.

This paper is organized systematically. A thorough background analysis and a review of relevant literature are given in Section 2 in relation to earlier studies on the ABC algorithm. In Section 3, the ABC algorithm's working process is outlined, providing an understanding of its underlying principles. The Enhanced ABC is presented in Section 4, along with an explanation of its Adaptive Position Update (APU) and Adaptive Exploration-Exploiting (AEE) features. Finally, a thorough description of the simulation results provides the empirical evidence supporting the proposed algorithm's effectiveness in Section 5.

2. Literature Survey

Population-based search algorithms have demonstrated remarkable efficacy in handling many optimization issues, such as congestion control in VANETs, in the past few decades. Recently, population-based algorithms like swarm intelligence and evolutionary algorithms have drawn particular attention from researchers. The main goals of the research are to optimize ABC parameters, look into new strategies, and compare outcomes to those of other optimization methods. The literature emphasizes ABC's popularity as a nature-inspired algorithm in the optimization field because of its adaptability, robustness, and continuous development.

G. Santhosh et al. [14] proposed a group-based wireless sensor network routing scheme for Energy Optimization Routing using Improved ABC (EOR-IABC). To identify possible Cluster Heads (CHs), the EOR-IABC combines a unique search policy with the Cauchy operator and Grenade Explosion Method (GEM). The level of exploration and exploitation for the CH selection method is then enhanced as it dynamically expands its search exploration from one place to another. Using self-adapting update techniques for regular CH updates depending on the fitness function minimizes the convergence delay. EOR-IABC is simulated using a simulation tool, and the experimental results are contrasted with those of the current IABCOCT and OCABC. The EOR-IABC performance outcomes demonstrate a notable improvement in live nodes, delivery of packets, average energy consumption and decreased latency.

Qiuyu Cui et al. [15] introduced an improved multi-objective ABC algorithm, a Bio-inspired based algorithm for route planning. Four techniques of the IMOABC algorithm, such as external achieve pruning, non-dominated ranking, crowding distance, and search strategies, are the main sources of the IMOABC algorithm. Standard test functions of size six are chosen for testing IMOABC, and each test function has two optimization objectives. The IGD is used as the evaluation criterion to compare the algorithms' levels of efficiency. IMOABC method performs better than former algorithms in resolving difficult multi-objective optimization issues.

C. Nandagopal et al. [16] presented a hybrid algorithm for routing that combines ACO and ABC optimization to transfer data from one location to another, which becomes more effective. In order to prevent congestion and link failure, the optimum routing process was used. The design of the fitness function depends on the residual energy source and stability of the link. The proposed approach is validated using an update function, fitness calculations, and solution encoding. NS2 simulator software is used to carry out simulation results. Results of the hybrid algorithm were shown to be particularly more effective in terms of delivery of packets and latency when compared to other existing VANET algorithms.

Saurabh Dadasaheb Patil et al. [17] proposed an improved routing method for VANET using micro-ABC and adaptive fuzzy-based message dissemination. An adaptive fuzzy-based multi-criteria decision-making technique was applied to select the cluster head. In optimal decision-making, this method combines the fuzzy visekriterijumskaoptimizacija method and Ikompromisnoresenje method with decision-making trial depending on fuzzy and evaluation laboratory model-based ANP, also known as fuzzy decision-making trial and evaluation laboratory-based analytic network process. To communicate from vehicle to vehicle during an emergency, a vehicle emergency dissemination protocol is used. Lastly, the optimal minimal path from the start to the endpoint is chosen using MABC. With Vehicular emergency dissemination protocol, each vehicle collects accident information from other vehicles in the same hop. Comparing the proposed method to other existing methods, simulation results obtained in MATLAB demonstrate notable improvements.

Ali Hamza et al. [18] developed an improved version of the Bees algorithm for solving Multiple Travelling Salesman Problems (MTSP) that makes use of a new local search technique. The proposed approach utilizes local search operators to accomplish it. In order to benefit from nearby solutions, these operators are employed. The Bees Algorithm (BA) uses two operators, namely 2-opt move and Ext-SO. In order to enhance the efficiency of the algorithm, a novel local searching operator called SBESTSO was introduced. Using several MTSP benchmark datasets, the effectiveness of the Bees algorithm with a novel local searching operator was assessed. For the same datasets, the outcome was compared with other optimization techniques. The results demonstrate the Bees algorithm's resilience to MTSP.

Chunfeng Wang et al. [19] proposed a new ABC depending on Bayesian Estimation (BEABC) algorithm. Initially, a new probability is determined using Bayesian estimation and is used in place of fitness ratios as the selection probabilities in ABC. Second, a directional guidance strategy was developed for onlooker and scout bees to assist bees in assimilating more helpful information while updating new food sources. Lastly, 24 single-objective test functions were used to assess BEABC's overall performance. Depending on the comparative result, BEABC performs better than other evolutionary algorithms.

Xinyu Zhou et al. [20] proposed a developed ABC variant depending on a multi-elite guidance system in order to effectively utilize the important data from multiple elite solutions. To improve exploitation without affecting exploration, the author proposed two changes to MGABC based on elite groups. First, two modified solution-searching methods are proposed for the employed and onlooker bee phases. The second search strategy is added to ABC's framework by incorporating a modified neighborhood search operator. When these strategies are combined, the proposed MGABC can greatly enhance ABC's performance. One real-world problem, fifty benchmark functions, and seven more well-known ABC variants were used in the comparison of the experiments. Based on experimentations, the proposed strategy produced better results on the majority of test functions.

S. Famila et al. [21] proposed an Improved ABC Optimization-Oriented Clustering (IABCOCT) method by utilizing the advantages of the Cauchy operator and Grenade Explosion Method (GEM) to enable the ideal selection of CHs. The ABC algorithm's convergence rate is increased, and it is kept out of local optima by integrating the Cauchy operator and GEM. The onlooker and Scout bee stages incorporate the advantages of the GEM and Cauchy operators for a remarkable enhancement in the point of exploitation and exploration throughout the CH selection procedure. According to simulation results, the IABCOCT algorithm outperforms state-of-the-art techniques of various metrics like throughput, loss of packets, delay, energy consumption, and network lifetime. These techniques include HCCHE, EPSOCT and CCT.

Long Cheng et al. [22] present an improved ABC by merging the Beetle Antennae Search algorithm (BAS). BAS-ABC selects the direction in which a bee should move while looking for food. It eliminates the uncertainty of searching to approximate the efficiency of the traditional ABC algorithm. This study examines the course of solution improvement by imitating the beetle's searching and detecting activity and drawing inspiration from the BAS algorithm. The proposed algorithm can reach the optimal solution faster than the original ABC. In this work, five test functions are used to confirm the accuracy and stability of the improved ABC algorithm after merging the BAS algorithm (BASABC). The functions are Ackley, Griewank, Rastrign, Rosenbrock and Sphere. The developed BAS-ABC approach shows superior performance compared to ABC and PSO algorithms.

Mohammed El Amine Fekair et al. [23] introduced FBQoS-Vanet, a QoS-based routing protocol designed to assist highway-related VANET applications. In finding routes that meet QoS requirements, the protocol employs the bio-inspired ABC technique. FBQoS-Vanet uses fuzzy logic to identify the optical path that satisfies QoS requirements. ABC-based algorithms are used to find paths that comply with QoS. Five Qualities of Service (QoS) metrics are used to select routes. They are buffer occupy rates, obtainable bandwidth, jitter, the delay from end to end and link expiration time. The proposed protocol's performance was evaluated by using the Network simulator OMNeT++. Two popular QoS-based VANET routing protocols, such as FCAR and RQ-AODV, are compared with a new protocol. Based on the results of the simulation, FBQoS-Vanet performs better than RQ-AODV and FACR for the parameters throughput, end-to-end latency, and transfer of packets.

HaoGao et al. [24] proposed two new updating equations for employed and onlooker bees. In order to speed up the worst-performing, onlooker, and employed bee convergence rates, intelligent learning techniques are incorporated. To balance their local and global searches, turbulent operators are used. In order to speed up the worst employed bee's convergence rate, an intelligent learning method is finally proposed. A number of benchmarking functions and two industrial problems were utilized to determine the developed algorithm's efficiency. The developed strategy performs better on theoretical and practical issues.

Table 1. Comparison of various routing algorithms designed for VANETs

Authors	Methodology	Merits	Demerits
G. Santhosh et al.	Developed a group-based WSN routing method for energy optimization using EOR-IABC, integrating a special search policy with the Cauchy operator and GEM for CH identification.	Improved live nodes, packet delivery, energy consumption, and reduced latency.	Increased computational complexity may limit scalability.
Qiuyu Cui et al.	Depending on bio inspired notions and search methodologies, presented an improved multi-objective ABC algorithm for route planning.	Enhanced resolution of complex multi-objective optimization issues.	Limitations in real-world routing applications.
C. Nandagopal et al.	Developed a novel routing algorithm merging ABC optimization with Ant colony optimization for efficient data transfer.	High delivery of packets and reduced end-to-end delay.	Restrictions in real-time traffic systems.
SaurabhDadasaheb Patil et al.	Advanced a VANET routing scheme using adaptive fuzzy-based message dissemination and micro-ABC.	Effective in finding optimal minimum routes.	Challenges in implementation in complex road scenarios.
Ali Hamza et al.	Employed a new local search technique in an enhanced Bees algorithm for solving MTSP, using 2-opt move and Ext-SO operators.	Greater fitness, faster execution, and quality solutions with fewer evaluations.	Operators are not versatile across different problem types.
Chunfeng Wang et al.	Provided a new selection probability for the ABC variant using Bayesian estimation. and directed guidance, introducing MR and λ parameters.	Balances exploration and exploitation effectively.	Improvement is needed for rotated and shifted problem-solving.
Xinyu Zhou et al.	Offered an ABC variant relying on a multi-elite guidance system to use information from several elite solutions efficiently.	Improved exploitation without compromising exploration.	Enhancements needed for applicability to real-world problems.
S. Famila et al.	Presented an improved ABC-based clustering method utilizing GEM and Cauchy operator for optimal CH selection.	Increases alive nodes and systematically improves packet delivery rate.	Potential exploration of ACO algorithm variants with differential strategies.
Long Cheng et al.	Introduced an improved ABC for increased solution accuracy by fusing it with the Beetle Antennae search algorithm.	Improves accuracy in finding the best solution.	Application to diverse real-world scenarios is needed.
Mohammed El Amine Fekair et al.	Designed FBQoS-Vanet, a QoS-based routing method for VANET applications for highways.	Minimal end-to-end latency, high throughput, and transfer of packets ratio.	Limited applicability in urban environments.
HaoGao et al.	Proposed new updating equations for the onlooker and employed bees using turbulent operators to accelerate convergence.	Balances local and global search efficiently.	Needs application to more real-world problems.
Chun-Feng Wang et al.	The improved ABC algorithm includes a novel searching model for onlooker bees that focuses on both optimal and sub-optimal solutions.	Enhances exploitation by onlooker bees.	Application of parameters ω, c1, and c2 needed for performance improvement.

Chun-Feng Wang et al. [25] provided a new search equation to onlooker bees which considers both optimal along with sub-optimal solutions during the cycle of operation. Furthermore, to improve global convergence, an opposition-based strategy and a chaotic system are used to construct the initial population. The optimal solution of the current iteration also uses a chaotic search to speed up the proposed algorithm's global convergence. The experimental results are tested using twenty benchmark functions. These benchmark functions can be classified as multimodal or unimodal. IABC's effectiveness was extensively verified by contrasting its results with those of three other novel ABC variants: GABC, COABC, and ABC/best/1, as well as the original ABC.

3. The Original ABC

Among the Bee algorithms that are most frequently utilized is the ABC algorithm. Karaboga proposed it, and it is based on how honey bees forage in a colony. In the ABC algorithm, where a food source may address the optimization problem in the search space, the nectar amount of a food source represents the fitness value of that solution [26]. The ABC contains three different kinds of searching bees. They are employed onlookers and the scout bees. The number of employed bees and onlooker bees in the colony is equal [27]. Employed bees use their memory for food searching near the source of food and communicate to the onlooker bees about the locations of the sources of food in the dance area as well as the amounts of nectar they contain. The onlooker bee selects which source of food to visit after observing dances. It often uses a roulette wheel selection process to identify food sources of the highest quality. Based on the amount of nectar contained in the source of food, each onlooker bee will choose it with a probability. Onlookers would be more likely to select higher-quality food sources [28]. The original ABC algorithm contains a controllable parameter called "limit". Food sources are said to be abandoned when they reach their limit and can no longer be improved, becoming scout bees that randomly look for new food sources to prevent local optima [29]. The scout bee searches the search area randomly and finds a novel solution [30].

3.1. Initialization Phase

Equation (1) is used to create the first food sources at random during the initialization phase. These food sources were added as the starting point for the optimization process.

$$x_{i,j} = x_j^{LB} + rand(0,1) \,.\, x_j^{UB} - x_j^{LB} \qquad (1)$$

Where, *i* ϵ*{1, 2, 3… N}*, *j* ϵ*{1, 2, 3… D}*, indicates how many food sources were employed during the optimization process and denotes the size of search space, rand (0, 1) is an evenly produced random variable within the interval [0, 1].

3.2. Employed Bee Phase

Equation (2) is utilized to generate novel sources of food v_i by each employed bee close to its current position x_i during this phase.

$$v_i^j = x_i^j + rand(-1,1) \times (x_i^j - x_k^j) \qquad (2)$$

Where, *k* ϵ*{1, 2… N}*, *j* ϵ*{1, 2… D}*, which are selected randomly and $k \neq i$, *rand (-1, 1)* is a random number within limit [-1, 1]. Upon obtaining v_i, a greedy selection process is then used to select between v_i and x_i. If $f(v_i) \leq f(x_i)$, v_i replaces x_i and joins the population, if not x_i is retained.

3.3. Onlooker Bee Phase

Equation (3) is used by every onlooker bee to find the sources of food depending on the probability which is depending on its fitness value.

$$p_i = \frac{Fit\ (x_i)}{\sum_{i=1}^{N} Fit\ (x_i)} \qquad (3)$$

Equation (4) is used to define the fitness values of the sources of food x_i.

$$f(x_i) = \begin{cases} \dfrac{1}{1 + f(x_i)} if\ \ f(x_i) \geq 0 \\ 1 + abs(f(x_i) else \end{cases} \qquad (4)$$

By using Equations (3) and (4), a source of food with a higher fitness value has a better chance of being chosen by onlooker bees.

Equation (2) is used to exploit selected food sources for better solutions, and Equation (4) is used to determine their fitness values. Then between x_i and v_i a greedy selection is used.

3.4. Scout Bee Phase

When the associated bee abandons its source of food and becomes a scout bee, it will not yield better solutions even within a predetermined limit value. In the search area, a novel food source is randomly generated using Equation (1).

By using the ABC Optimization algorithm, solutions are repeatedly improved by mimicking the foraging activity of bees and updating employed bee solutions according to the fitness values illustrated by Algorithm 1.

In vehicular Ad hoc networks, congestion is systematically reduced with the help of the ABC optimization algorithm. Initially, ABC minimizes the risk of congestion along particular paths by optimizing dynamic routes for vehicles. Later, the vehicles can exchange real-time traffic data through proactive communication.

Through cooperative communication, vehicles are equipped with the knowledge of traffic patterns, which helps them make well-informed decisions about their routes. By increasing VANET efficiency, ABC optimization promotes more effective traffic flow and enhanced network performance as a whole.

Algorithm 1: ABC Bee Colony Optimization Algorithm

1. Initialize parameters: *N*, *D*, and *limit*.
2. Initialize position of solution $i \in \{1, 2, 3 \ldots N\}$ using equation
$$x_{i,j} = x_j^{LB} + rand(0,1) \cdot x_j^{UB} - x_j^{LB}.$$
3. While termination criteria are not met, do.
4. Create a novel food source. v_i for every employed bee close to its current position x_i and evaluate it by using the Equation: $v_i^j = x_i^j + rand(-1,1) \times (x_i^j - x_k^j)$
5. The procedure of greedy selection is employed to choose between x_i and v_i.
6. Calculate probability values p_i using equation
$$p_i = \frac{Fit\,(x_i)}{\sum_{i=1}^{N} Fit\,(x_i)}$$
depending on fitness values using Equation
$$f(x_i) = \begin{cases} \dfrac{1}{1+f(x_i)} iff(x_i) \geq 0 \\ 1 + abs(f(x_i)\; else \end{cases}$$
7. A greedy selection process is applied between x_i and v_i.
8. Remember the optimal solution obtained.
9. To find the solution that has been abandoned, raise the value of the limit parameter. If the scout bee solution already exists, replace it with the new one created with the Equation $x_{i,j} = x_j^{LB} + rand(0,1) \cdot x_j^{UB} - x_j^{LB}$.
10. Remember the effective solution obtained so far.
11. End while
12. Output the better solution

One major disadvantage of VANETs is their dynamic nature, which frequently results in changes to the network topology and disruptions to connectivity. This problem is addressed by adaptive position updates, which skillfully adjust the frequency at which vehicles broadcast their location. Instead of utilizing set time intervals, vehicles adaptively update their positions in response to changes in direction and speed, increasing the effectiveness of location-based services without adding needless overhead. Furthermore, VANETs face issues with network resource allocation and energy consumption. The dynamic conditions of VANETs may pose a challenge for conventional optimization algorithms. However, the algorithm can modify the ratio of exploration to exploitation depending on the network's current state by using an adaptive exploration-exploitation optimization. VANETs' adaptability allows them to transmit data more effectively and allocate resources more wisely while consuming less energy. By applying exploration-exploitation optimization techniques and adaptive position updates, it is possible to get around some of the limitations of VANETs effectively. VANETs can get around these restrictions and function more robustly and resiliently in dynamic vehicular environments by using adaptive mechanisms.

4. Proposed Algorithm

In order to optimize congestion control and increase network efficiency in dynamic vehicular environments, this work proposes the Enhanced Artificial Bee Colony with Adaptive Position Update and Adaptive Exploration: Exploiting algorithm (EABC-APUAEE). First, a new Equation (5) for Adaptive Position Update (APU) is presented. It improves convergence towards optimal solutions by dynamically optimizing the ABC algorithm's locations. This improvement adjusts individual positions based on past performance. Eventually, the ABC algorithm's dynamic balance between exploration and exploitation is adjusted via the Adaptive Exploration-Exploiting (AEE) Equation (6).

4.1. Adaptive Position Update Equation (APU)

ABC algorithm is sensitive to parameter settings, wherein poorly selected values may result in sub-optimal performance, which is one of its drawbacks. Furthermore, ABC may experience problems with premature convergence. ABC is improved by the APU Equation (5), which dynamically modifies individual locations depending on past performance, which increases convergence efficiency and is shown through Equation (5).

$$\begin{aligned}(x_{i,j})^{t+1} = (x_{i,j})^t + \varphi_{i,j}\left((x_{i,j})^t - x_{k,j}\right) \\ +\emptyset_{i,j}\left(x_{globalbest,j} - (x_{i,j})^t\right) \\ +\psi_{i,j}\left(x_{rand,j} - (x_{i,j})^t\right) \\ +\lambda_{i,j}\left(x_{localbest,j} - (x_{i,j})^t\right)\end{aligned} \tag{5}$$

Where,

- $(x_{i,j})^{t+1}$ represents the updated location of the i^th candidate food sources of the j^th dimension at the next iteration (t+1).
- $(x_{i,j})^t$ denotes the current location of the i^th candidate food sources of the j^th dimension at the next iteration (t).
- $x_{k,j}$ represents the adjacent food source's position.
- $\left(\varphi_{i,j}(x_{i,j})^t - x_{k,j}\right)$ denotes the local search component which affects the food sources according to the difference between its present position $(x_{i,j})^t$.
- A neighboring food source position $x_{k,j}$.
- $\emptyset_{i,j}\left(x_{globalbest,j} - (x_{i,j})^t\right)$ denotes the component of global influence, which directs the existing solution in the j^th dimension towards the best-performing solution.
- $\psi_{i,j}\left(x_{rand,j} - (x_{i,j})^t\right)$ adds the randomness to the update. It usually involves multiplying the position of a random solution $x_{rand,j}$ by a coefficient $\psi_{i,j}$ and changing the location of the existing solution.
- $\lambda_{i,j}\left(x_{localbest,j} - (x_{i,j})^t\right)$ refers to the element of local best influence.

- The current solution position is adjusted by comparing the locations of the local best solution $\left(x_{localbest,j} - (x_{i,j})^t\right)$ and the current solution $(x_{i,j})^t$.
- $\varphi_{i,j}, \emptyset_{i,j}, \psi_{i,j}, \lambda_{i,j}$ are parameters which are random values with uniform distributions within the interval.

There may be a conflict in the movement of candidate food sources if local and global best are in opposite directions. Because of this, the ABC algorithm experiences slow convergence speed as it tries to determine where to use the data from local best or global best. One possible solution to this problem could be to dynamically modify the coefficients depending on the fitness values of the best local and global food sources. APU Equation adds dynamic influences to improve solution exploration. Every term in this equation has a significant influence on how candidate solutions behave.

ABC algorithm benefits from this equation at various stages. By taking into account both local and global influences, it promotes solution exploration during the employed bee phase and increases the set of possible solutions. The dynamic equation helps to choose and update solutions during the onlooker bee phase, ensuring a balance between exploration and exploitation. This APU equation greatly helps in exploring search space during the scout bee phase, adjusting to modifications, and improving solutions for better convergence.

Adaptive Position Update Equation can effectively address congestion control problems in VANETs. The effective mobility and traffic flow optimization of VANETs are dependent on vehicle-to-vehicle communication. The dynamic nature of the equation helps to reduce congestion in the following ways.

The local component represents the first vehicles exploring adjacent regions $\varphi_{i,j}(x_{i,j})^t - x_{k,j}$, which reflects the idea of modifying routes based on the traffic circumstances of nearby vehicles. Vehicles in congested areas can dynamically modify their routes in order to reduce traffic jams and increase network efficiency. Vehicles are guided towards optimal routes by the global influence term $\emptyset_{i,j}\left(x_{globalbest,j} - (x_{i,j})^t\right)$.

This means that in VANETs, Vehicles can modify their routes in response to data from other vehicles that are facing less traffic which helps to reduce congestion. Vehicles can randomly explore different routes because of the randomness component. $\psi_{i,j}\left(x_{rand,j} - (x_{i,j})^t\right)$.This randomness gives the system flexibility, enabling vehicles to find and adopt new routes actively. Furthermore, local information is important and is emphasized by the local influence term

$$\lambda_{i,j}\left(x_{localbest,j} - (x_{i,j})^t\right).$$

This represents vehicles modifying their routes in congested situations in response to neighboring vehicles' traffic conditions, resulting in a more responsive, adaptable VANET. Throughout the optimization process, adaptive position updates are used to dynamically adjust the position of bees based on fitness amounts of best local, global and random food sources, which is illustrated in Algorithm 2.

Algorithm 2: Adaptive Position Update (APU) Optimization Algorithm

1. Input parameters: $x_{i,j}, x_{localbest,j}, x_{globalbest,j}, x_{rand,j}, \varphi_{i,j}, \emptyset_{i,j}, \psi_{i,j}, \lambda_{i,j}$
2. Calculate the local search by using the equation $\varphi_{i,j}(x_{i,j})^t - x_{k,j}$.
3. Calculate the global search by using the equation $\emptyset_{i,j}\left(x_{globalbest,j} - (x_{i,j})^t\right)$.
4. Calculate the random exploration using the equation $\psi_{i,j}\left(x_{rand,j} - (x_{i,j})^t\right)$.
5. Calculate the local attraction $\lambda_{i,j}\left(x_{localbest,j} - (x_{i,j})^t\right)$.
6. Update the position by using the equation
$$(x_{i,j})^{t+1} = (x_{i,j})^t + \varphi_{i,j}(x_{i,j})^t - x_{k,j} + \emptyset_{i,j}\left(x_{globalbest,j} - (x_{i,j})^t\right) + \psi_{i,j}\left(x_{rand,j} - (x_{i,j})^t\right) + \lambda_{i,j}\left(x_{localbest,j} - (x_{i,j})^t\right).$$
7. Returns updated position $(x_{i,j})^{t+1}$

4.2. Adaptive Exploration-Exploiting (AEE) Optimization Equation

To avoid premature convergence and determine the optimal ratio of exploration to exploitation, the proposed Adaptive Exploration-Exploiting (AEE) optimization is shown in Equation (6).

$$updatedfood_{i,j} = \frac{\alpha_j+\beta_j}{2} + \delta * RS\left[\left(\omega * (-1)^{l1}\left(g_1\alpha_j - rand1 * currentfood_{i,j}\right)\right) + \left((1-\omega) * (-1)^{l2}\left(g_2\beta_j - rand2 * currentfood_{i,j} + \varepsilon\right)\right)\right] \quad (6)$$

Where,

- $updated\,food_{i,j}$ is the updated food position of the j^{th} dimension of i^{th} food source.
- Among the food sources chosen at random, α represents the position with the highest level of fitness.
- β represents food sources' fitness values that were chosen at random.
- δ is the step size that is dynamically adjusted based on the success rate.

- RS is the rate of success component which affects the algorithm's over all exploration-exploitation balance.
- ω is a weighting factor ranging from 0 to 1 that modifies the relative importance of the two search strategy components.
- l1 and l2 are two integers chosen randomly as 0 to 1.
- g1and g2 are two parameters which affect the searching strategy.
- Two random variables, rand1 and rand2, are used to choose values between 0 and 1.
- $\mathrm{currentfood}_{i,j}$ is j^{th} element of i^{th} food source.
- ε is an exploration term that introduces controlled exploration.

The proposed Equation (6) improves the ABC's performance in each of its three main phases. In order to promote deliberate exploration and avoid premature convergence, the proposed equation introduces adaptive exploration based on the success rate during the employed bee phase.

The onlooker bee phase is guided towards successful outcomes by a balanced exploration-exploitation strategy using controlled randomization and historical success coefficients.

Through encouraging scout bees to actively participate in exploring new areas and energizing the search process, the exploration factor benefits the scout bee stage. In VANETs, higher vehicle densities can lead to congestion, which can impair network efficiency and cause communication delays.

VANET congestion control benefits from the exploration-exploitation Equation (6) with dynamic and adaptive features. Adaptive exploration is incorporated into this equation to allow VANET nodes to explore alternative communications paths in response to congestion intelligently.

The success rate, which is a measure of the past effectiveness of particular routes, affects the purposeful exploration strategy. Nodes can more easily adjust to changing network conditions by using dynamic step size to modify communication parameters based on success rate.

The controlled randomness ensures that the exploration-exploitation strategy stays flexible by helping nodes locate less congested routes. Historical success coefficients navigate nodes toward paths that have proven to be efficient, thereby increasing the probability of finding routes free of traffic.

Adaptive exploration-exploitation optimization dynamically adjusts the balance between the exploration of new solutions and the exploitation of known solutions, which is illustrated in Algorithm 3.

Algorithm 3: Adaptive Exploration-Exploitation (AEE) Optimization Algorithm

1. Initialize the population of food sources with random positions.
2. Initialize parameters and constants:

α,β,δ, *l1, l2, g1, g2, RS.*

3. While termination conditions are not met, do
4. For every food source i in the population:
   i. Take the random number *rand1* between 0 and 1.
   ii. Take the random number *rand2* between 0 and 1
5. Calculate the exploration term ε.
6. Update the position of the food source *i* using the equation

$$updatedfood_{i,j} = \frac{\alpha_j+\beta_j}{2} + \delta * RS\left[\left(\omega * (-1)^{l1}\left(g_1\alpha_j - rand1 * currentfood_{i,j}\right)\right) + \left((1-\omega) * (-1)^{l2}\left(g_2\beta_j - \ rand2 * currentfood_{i,j} + \varepsilon\right)\right)\right]$$

7. Analyze each food source's fitness by using the equation

$$f(x) = \begin{cases} \dfrac{1}{1+f(x_i)} & iff(x_i) \geq 0 \\ 1 + abs(f(x_i)else & \end{cases}$$

8. Identify the best food source based on fitness values.
9. Update parameters based upon requirement.
10. End while
11. Output the best updated food source.

The actual process with the proposed EABC-APUAEE method for congestion control in VANETs is shown in Figure 3. For VANET congestion control, the block diagram of the EABC algorithm with APUAEE is essential.

Through the integration of adaptive mechanisms, the algorithm is capable of dynamically adapting to the ever-changing network conditions, including variations in vehicle density and traffic patterns, thereby guaranteeing effective management of congestion. The algorithm's capacity to make decisions in real-time is essential in preserving efficient traffic flow.

The algorithm is designed by initializing parameters in the "Initialization Phase". Then, it moves on to the "Position Update Phase," where current vehicle position data is obtained, and several variables are evaluated to see if a position update is required.

These variables include time-lapse, distance traveled, and network conditions. The vehicle updates its position if it exceeds the update frequency threshold.

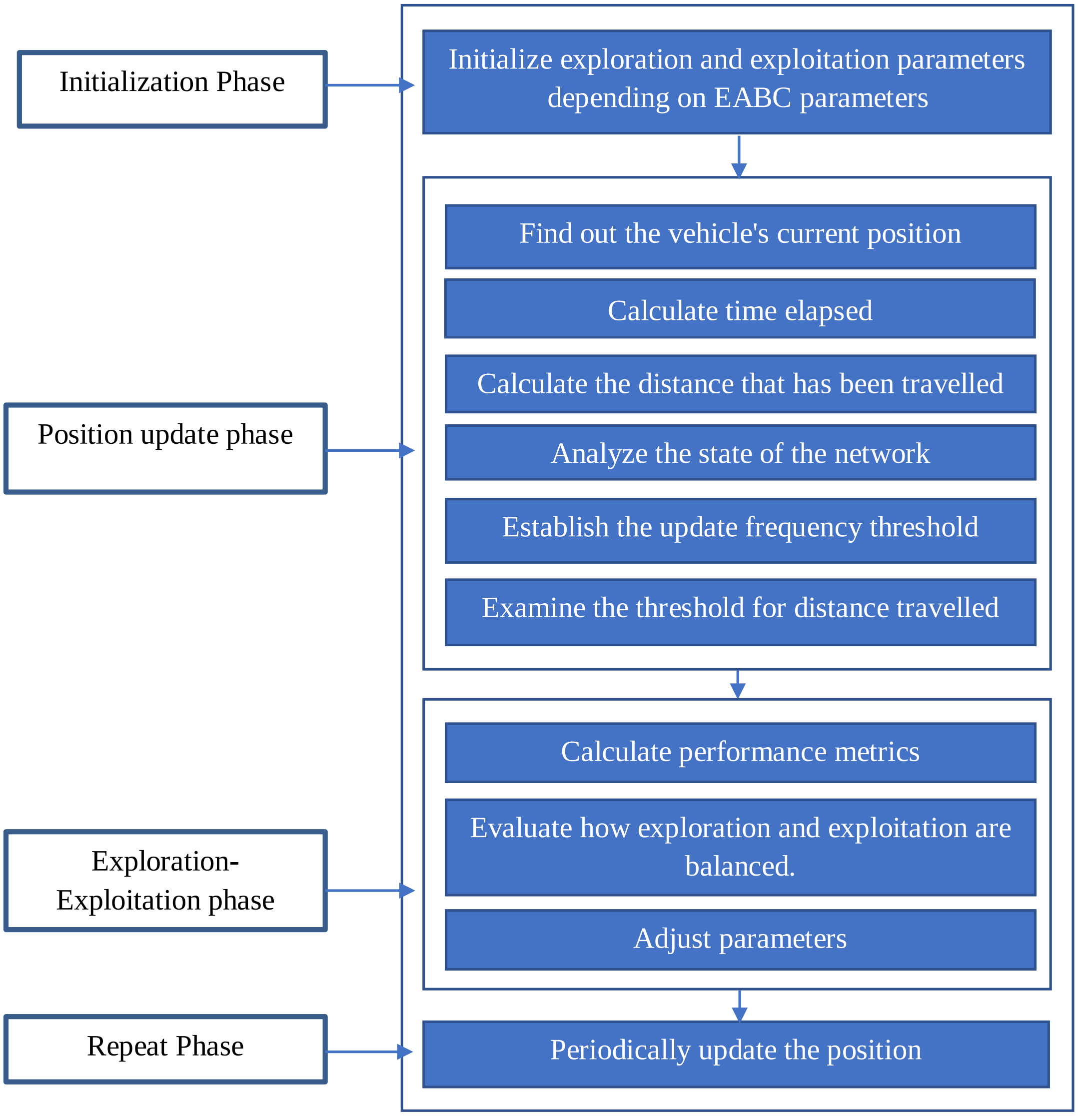

Fig. 3 Block diagram of proposed EABC-APUAEE

In the "Exploration-Exploitation Phase", the algorithm evaluates performance metrics and modifies the parameters for exploration and exploitation in accordance with the established balance between the two. This phase makes sure that the exploration-exploitation trade-off is optimized and that the network can adjust to changing conditions. After that, the procedure moves into the "Repeat Phase", where the position update and exploration-exploitation Phases are repeatedly carried out in order to adjust to the environment's changing conditions continuously.

4.3. Working of EABC-APUAEE Using Sphere Function

- The Enhanced ABC optimization scenario employs a swarm size of six,
- Initialization of the population with Equation $f(x) = x_1^2 + x_2^2 + x_3^2$,
- The objective function is $\min f(x) = \sum_{i=1}^{3} x_i^2$; $0 \le x_i \le 10$.

Swarm size includes three employed, three onlookers and three scout bees.

Table 2 illustrates the working of EABC-APUAEE optimization. First, a vector of the population is created. The employed bees in this population hold random solutions.

These solutions' fitness is evaluated by the objective function, which establishes the basis for their quality. Bees explore their local solutions during the employed bee phase. They update their positions using the adaptive position update Equation (5), which considers trail data and current fitness value. In the meanwhile, onlooker bees are directed to potential locations by the fitness information that influences their probabilistic solution selection. Through an adaptive exploration-exploitation Equation (6), the algorithm dynamically balances exploration and exploitation, influencing the decisions made by the onlooker bee. During the scout bee stage, bees find solutions with limited improvement and mark them for exploration. The adaptive position update equation and exploration-exploitation equation continue to influence the search process. The iterative cycle continues until convergence or a defined termination criterion. During this repeating cycle, the algorithm explores and exploits the solution space to ensure that the optimal solution is selected.

Table 2. Working of EABC-APUAEE

		Initial Vector Population	**Objective Function**	**Fitness Value**	**Trail**
		1 0 8 5 4 7 2 1 4	65 90 21	0.01515 0.01111 0.04761	0 0 0
Employed Bee Phase	**First bee solution**	1 0 8	65	0.01515	1 0 0
	Second bee solution	5 4 7	90	0.01111	1 1 0
	Third bee solution	2 1 0.72	21	0.1534	1 1 0
Probability Value **0.18** **0.16** **1**					
Onlooker Bee Phase	**First bee solution**	0.4 0 8 5 4 7 2 1 0.72	64.16 90 5.5184	0.01534 0.01111 0.01534	0 1 0
	Second bee solution	0.4 0 8 1.39 4 7 2 1 0.72	64.16 66.93 5.5184	0.01534 0.01472 0.01534	0 1 0
	Third bee solution	0.4 0 8 1.39 4 7 2 1 0.72	64.16 66.93 5.5184	0.01534 0.01472 0.01534	1 1 0
Scout Bee Phase	**First bee solution**	0.4 0 8	64.16	0.01534	1 1 0
	Second bee solution	1.39 4 7	66.93	0.01472	1 1 0
	Third bee solution	2 1 0.72	5.5184	0.01534	1 1 0
Memorize the Best Solution		2 1 0.72	5.5184	0.01534	

5. Simulation Results

In this study, the proposed algorithm's results are simulated using MATLAB. The proposed EABC-APUAEE algorithm is evaluated using parameters like the number of vehicles, their speed, and packet size. Data is processed through simulation. A total of 300 vehicles were taken into consideration during the simulation process, and the speed range that was taken into consideration was 60 to 120 km/h. There are ten simulation runs, a simulation duration of one hundred seconds, and a packet size of 1024 bytes used in the simulation.

The proposed methodology EABC-APUAEE is compared with ABC. Three metrics are examined for performance analysis: packet delivery ratio and end-to-end delay and throughput.

5.1. Packet Delivery Ration (PDR)

By using an EABC with APU and AEE optimization to dynamically optimize node placements, PDR in VANETs is enhanced. PDR is calculated by using Equation (7).

This increases communication efficiency and reliability in dynamic vehicular environments. This adaptive strategy balances exploration and exploitation for optimal packet delivery and provides an efficient search of optimal paths.

In order to determine PDR, the total number of packets received at the source and the number of packets received at the destination are compared, as shown in Table 3. When compared to existing ABC, the PDR in this proposed work EABC-APUAEE has significantly improved, as illustrated in Figure 4.

The proposed EABC-APUAEE has an average PDR of 41.9%, and an average PDR of ABC is 32%. This means that EABC-APUAEE has an average PDR that is 30.78% higher than ABC.

$$Packet\ delivery\ ratio = \frac{Number\ of\ packets\ successfully\ delivered\ by\ EABC}{Total\ number\ of\ packets\ sent} 100\% \quad (7)$$

Table 3. PDR with respect to speed

Speed (km/h)	Improvement of Proposed EABC-APUAEE Over ABC Packet Delivery Ratio (%)	
	ABC	EABC-APUAEE
20	0.24	0.32
40	0.26	0.36
60	0.31	0.39
80	0.36	0.43
100	0.43	0.59
120	0.44	0.68

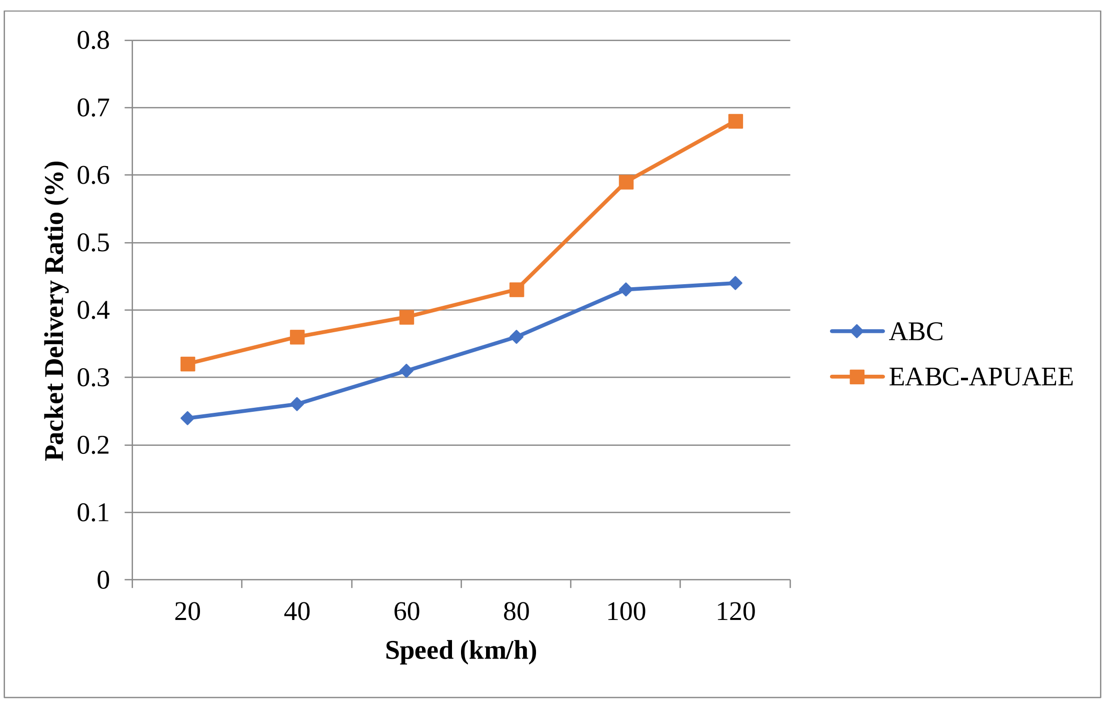

Fig. 4 PDR

5.2. End-to-End Delay (EED)

EED in VANETs are minimized by utilizing an EABC algorithm with APU and AEE optimization. EED is calculated by using Equation (8). In dynamic vehicular environments, this dynamic node position optimization promotes effective communication routes, reducing delays and improving overall performance. EABC-APUAEE performs better than the ABC method when it comes to transmitting data with the least amount of delay from sender to recipient using time-based packets, as shown in Table 4. Soon, the neighbor's location will be predicted. The average EED for ABC is 32.6667 milliseconds, while the average Need for EABC-APUAEE is 16.1333 milliseconds. This difference indicates a 50.54% reduction in EABC-APUAEE's EED as compared to ABC, as illustrated in Figure 5.

$$End - to - End\ dealy = Transmission\ delay + Propogation\ delay + Queing\ delay \quad (8)$$

5.3. Throughput

Throughput in VANETs is improved through the EABC algorithm with APU and AEE optimization. Throughput is calculated by using Equation (9). This is achieved by dynamically optimizing node positions, encouraging effective communication routes, and reducing delays, all of which contribute to an overall increase in network throughput in dynamic vehicular environments, as shown in Table 5.

This adaptive approach balances optimal throughput while ensuring an efficient search of optimal paths. Throughput is the amount of data that can flow in a predetermined amount of time. When compared to the existing ABC, the proposed method EABC-APUAEE greatly improves overall throughput performance, as illustrated in Figure 6.

ABC has an average throughput of 3.26441 mb/sec, whereas EABC-APUAEE has an average throughput of 4.4799 mb/sec. This difference indicates a 37.21% increase in EABC-APUAEE's throughput over ABC.

$$\text{Throughput} = \frac{\text{Number of packets successfully routed by EABC}}{\text{Total time taken to route the packets}} \quad (9)$$

Table 4. EED with respect to traffic density

Vehicle Density	Improvement of proposed EABC-APUAEE over ABC	
	End-to-End Delay (milliseconds)	
	ABC	EABC-APUAEE
50	29	12
100	31	14
150	32	15
200	35	17
250	36	21
300	39	23

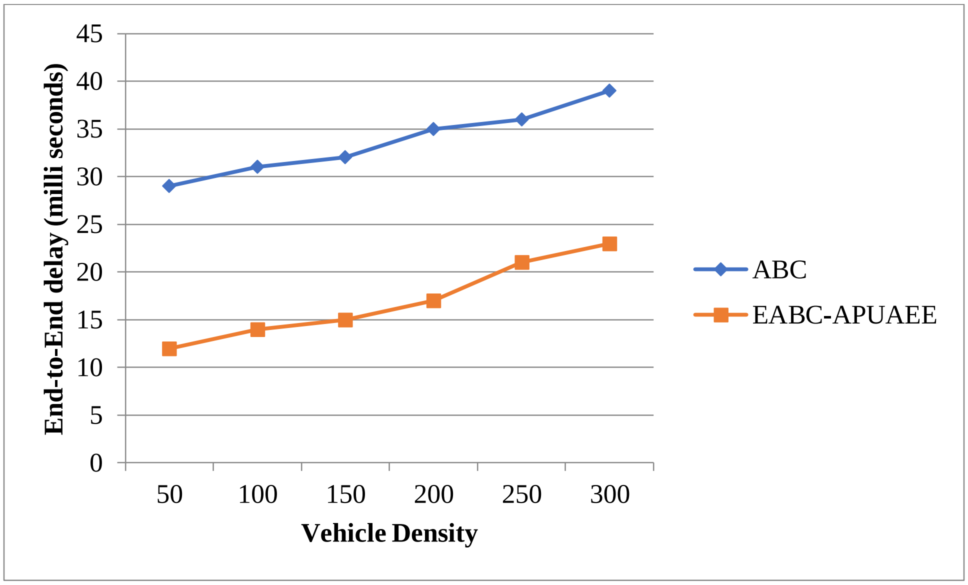

Fig. 5 End-to-end delay

Table 5. Throughput with respect to traffic density

Vehicle Density	Improvement of Proposed EABC-APUAEE over ABC Throughput (mb/sec)	
	ABC	EABC-APUAEE
50	2.7132	3.2768
100	2.6859	3.291
150	3.1416	3.258479
200	3.289	3.440609
250	4.1208	6.8797
300	4.5654	8.9164

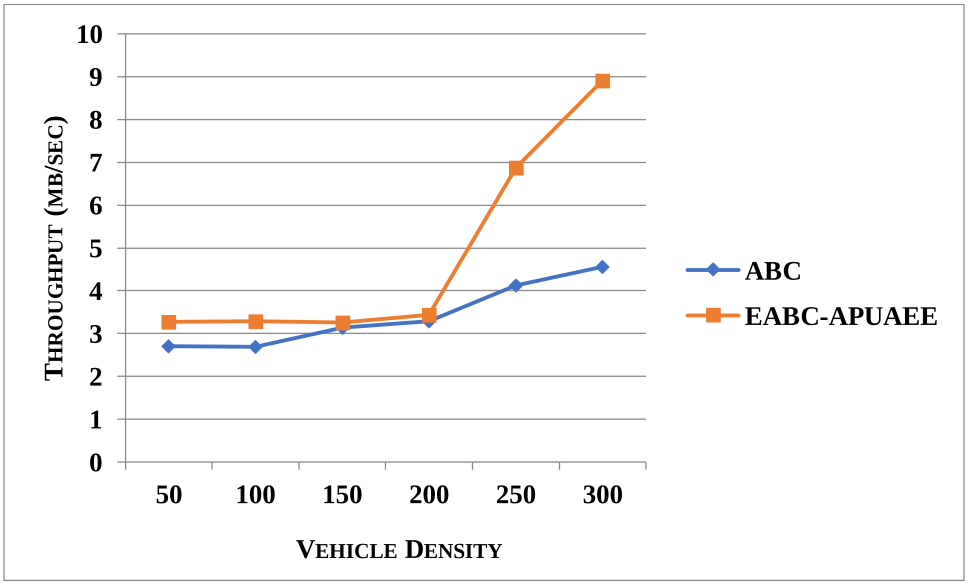

Fig. 6 Throughput

Table 6. Improvement of parameters with respect to traffic density

Traffic Density	Improvement of Proposed EABC-APUAEE Over ABC					
	Average PDR		Average EED		Average Throughput	
	ABC	EABC-APUAEE	ABC	EABC-APUAEE	ABC	EABC-APUAEE
300	32%	41.9%	32.6667 milliseconds	16.1333 milliseconds	3.26441 mb/sec	4.4799 mb/sec

The overall performance parameters used in this work are PDR, EED, and throughput, which are critical in evaluating the effectiveness and reliability of communication protocols in VANETs. There are important insights into how congestion affects network performance when comparing the performance metrics between ABC and EABC-APUAEE. The efficiency of congestion management strategies is demonstrated by the observed improvements in PDR, throughput, and EED for EABC-APUAEE when compared to ABC, as shown in Table 6. The average values of PDR, EED and Throughput are shown in Figure 7. By enhancing its dependability and efficiency, the VANET can now facilitate seamless communication between vehicles and infrastructure elements, even in challenging and congested scenarios.

In contrast to genetic algorithms that might undergo premature convergence and necessitate manual adjustment of parameters, the proposed approach offers flexibility by means of dynamically altering its search behavior. Compared to Particle Swarm Optimization, which works well for continuous optimization but struggles with discrete problems, the proposed model's adaptive exploration-exploitation optimization offers a better balance for both types of optimization tasks. For combinatorial optimization problems, Ant Colony Optimization is a great technique, but the proposed model's adaptive position update provides a more dynamic approach, especially in dynamic environments like Vehicular Ad hoc Networks (VANETs).

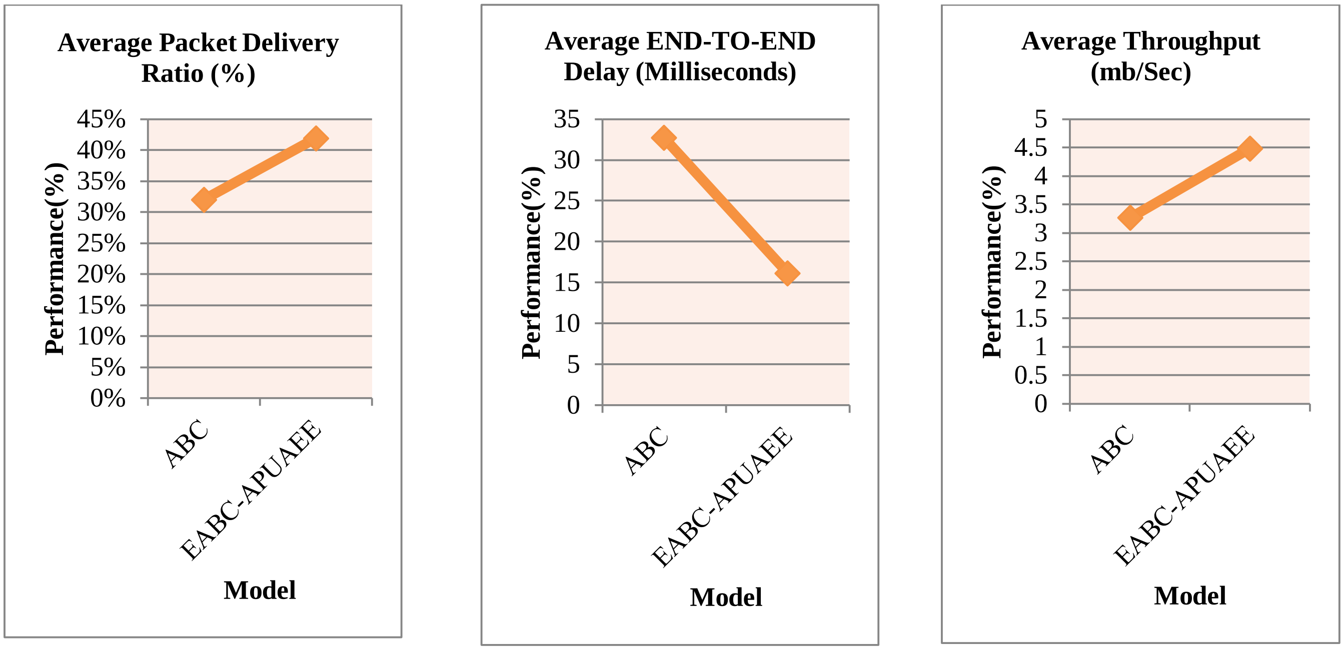

Fig. 7 Average PDR, EED and throughput

6. Conclusion

By incorporating the Adaptive Position Update Equation and the Adaptive Exploration-Exploiting Optimization Equation, the EABC Optimization Algorithm has proven to be effective in mitigating the limitations of traditional ABC methods. The adaptive position update equation increases convergence efficiency and enables a more sophisticated solution space search by dynamically changing individual locations based on historical performance. The exploration-exploiting optimization equation simultaneously provides a dynamic way to balance exploration and exploitation, so the proposed methodology may adapt its search strategy to various optimization landscapes.

Compared to ABC, the packet delivery ratio of EABC-APUAEE increased significantly to 30.78%. A higher packet delivery ratio suggests more effective use of the network's resources, which lowers the possibility of congestion and data loss. Compared to ABC, the throughput of EABC-APUAEE increased significantly to 37.21%. More data can be transferred over the network at a higher throughput, enabling quicker vehicle-to-vehicle communication. In comparison to ABC, the end-to-end delay of EABC-APUAEE dropped to 50.54%. Reduced latency results in faster message and data delivery, which is crucial for VANET congestion control. Reducing delays makes it possible for vehicles to make decisions more quickly, which improves traffic control and eases congestion. The proposed methodology effectively controls traffic congestion in real-time VANET scenarios by adjusting search behavior and the exploration-exploitation trade-off dynamically to optimize resource allocation and routing paths. The algorithm's adaptive nature enables it to quickly adjust to changing traffic patterns and network conditions, improving overall efficiency, reducing congestion, and improving network performance. The EABC-APUAEE might have certain limitations despite its efficacy. The quality of the input data regarding traffic conditions and the accuracy of the congestion detection mechanism have a significant impact on the algorithm's performance. Future work may focus on improving adaptive mechanisms through machine learning, exploring real-time system applications, and expanding multi-objective optimization capabilities.

References

[1] Ayoub Alsarhan et al., "A New Spectru, Management Scheme for Road Safety in Smart Cities," *IEEE Transactions on Intelligent Transport Systems*, vol. 19, no. 11, pp. 3496-3506, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[2] Mostafa M.I. Taha, and Yassin M.Y. Hasan, "VANET-DSRC Protocol for Reliable Broadcasting of Life Safety Messages," *IEEE International Symposium on Signal Processing and Information Technology*, Giza, Egypt, pp. 104-109, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[3] Leandro A. Villas, Tiago P.C. de Andrade, and Nelson L.S. da Fonseca, "An Efficient and Robust Protocol to Disseminate Data in Highway Environments with Different Traffic Conditions," *IEEE Symposium on Computers and Communications*, Funchal, Portugal, pp. 1-6, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[4] Leandro Aparecido Villas et al., "Drive: An Efficient and Robust Data Dissemination Protocol for Highway and Urban Vehicular Ad-Hoc Networks," *Computer Networks*, vol. 75, pp. 381-394, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[5] 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]

[6] Ramon Bauza, Javier Gozalvez, and Joaquin Sanchez-Soriano, "Road Traffic Congestion Detection through Cooperative Vehicle-to-Vehicle Communications," *IEEE Local Computer Network Conference*, pp. 606-612, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[7] Felipe Cunha et al., "Data Communication in VANETs: Survey, Applications and Challenges," *Ad Hoc Networks*, vol. 44, pp. 90-103, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[8] Mohamed Aissa et al., "SOFCluster: Safety Oriented, Fuzzy Logic Based Clustering Scheme for Vehicular Ad Hoc Networks," *Transactions on Emerging Telecommunications Technologies*, vol. 33, no. 3, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[9] Hoang Phuc Hau Luu, Abdlehak Sakhi, and Mukhlisulfatih Latief, "Optimizing Group Management and Cryptographic Techniques for Secure and Efficient MTC Communication," *International Journal of Computer Engineering in Research Trends*, vol. 11, no. 2, pp. 1-8, 2024. [CrossRef] [Publisher Link]

[10] D. Karaboga, and B. Basturk, "On the Performance of Artificial Bee Colony (ABC) Algorithm," *Applied Soft Computing*, vol. 8, no. 1, pp. 687-697, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[11] Dervis Karaboga, and Bahriye Basturk, "Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constructed Optimization Probles," *Foundations of Fuzzy Logic and Soft Computing, Lecture Notes in Computer Science Berlin*, Cancun, Mexico, pp. 789-798, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[12] Christian Blum, and Andrea Roli, "Metaheuristics in Combinatorial Optimization: Overview and Conceptual Comparison," *ACM computing Surveys*, vol. 35, no. 3, pp. 268-308, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[13] Dervis Karaboga, "A Comprehensive Survey: Artificial Bee Colony (ABC) Algorithm and Applications," *Artificial Intelligence Review*, vol. 42, pp. 21-57, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[14] G. Santhosh, and K.V. Prasad, "Energy Optimization Routing for Hierarchical Cluster Based WSN Using Artificial Bee Colony," *Measurement: Sensors*, vol. 29, pp. 1-8, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] N. Mondal et al., "Characteristics and Nature of Routing Protocols Used in VANET: A Comprehensive Study," *International Journal of Computer Engineering in Research Trends*, vol. 2, no. 5, pp. 284-287, 2015. [Google Scholar] [Publisher Link]

[16] 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]

[17] Saurabh Dadasaheb Patil, and Lata Ragha, "Adaptive Fuzzy-Based Message Dissemination and Micro Artificial Bee Colony Algorithm Optimised Routing Scheme for Vehicular Ad Hoc Network," *IET Communications*, vol. 14, no. 6, pp. 994-1004, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[18] Ali Hamza, Ahmed Haj Darwish, Omar Rihawi, "A New Local Search for the Bees Algorithm to Optimize Multiple Travelling Salesman Problem," *Intelligent Systems with Applications*, vol. 18, pp. 1-12, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Chunfeng Wang, Pengpeng Shang, and Peiping Shen, "An Improved Artificial Bee Colony Algorithm Based on Bayesian Estimation," *Complex & Intelligent Systems*, vol. 8, no. 6, pp. 4971-4991, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[20] Xinyu Zhou et al., "Enhancing Artificial Bee Colony Algorithm with Multi-Elite Guidance," *Information Sciences*, vol. 543, pp. 242-258, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[21] K. Samunnisa, and Sunil Vijaya Kumar Gaddam, "Leveraging Quantum Computing for Enhanced Cryptographic Protocols in Cloud Security," *International Journal of Computer Engineering in Research Trends*, vol. 11, no. 5, pp. 1-8, 2024. [Publisher Link]

[22] Elhadj Benkhelifa, Lokhande Gaurav, and S.D. Vidya Sagar, "BioShieldNet: Advanced Biologically Inspired Mechanisms for Strengthening Cybersecurity in Distributed Computing Environments," *International Journal of Computer Engineering in Research Trends*, vol. 11, no. 3, pp. 1-9, 2024. [Publisher Link]

[23] Mohammed El Amine Fekair et al., "An Efficient Fuzzy Logic-Based and Bio-Inspired QoS-Compliant Routing Scheme for VANET," *International Journal of Embedded Systems*, vol. 11, no. 1, pp. 46-59, 2019. [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, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[25] Chun-Feng Wang, and Yong-Hong Zhang, "An Improved Artificial Bee Colony Algorithm for Solving Optimization Problems," *IAENG International Journal of Computer Science*, vol. 43, no. 3, pp. 336-343, 2016. [Google Scholar] [Publisher Link]

[26] D.G. Brodland, V. Madan, and BK Armstrong, "SpectraScanNet: Enhancing Early Skin Cancer Detection through Spectral Imaging and Deep Learning," *International Journal of Computer Engineering in Research Trends*, vol. 11, no. 3, pp. 29-37, 2024. [Publisher Link]

[27] Wenjie Yu et al., "An Improved Artificial Bee Colony Algorithm Based on Factor Library and Dynamic Search Balance," *Mathematical Problems in Engineering*, vol. 2018, no. 1, pp. 1-16, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[28] Tomasz Bosakowski, David Hutchison, and P. Radhika Raju, "Cyberecoguard: Evolutionary Algorithms and Nature-Mimetic Defenses for Enhancing Network Resilience in Cloud Infrastructures," *International Journal of Computer Engineering in Research Trends*, vol. 11, no. 3, pp. 10-19, 2024. [Publisher Link]

[29] Jun Luo, Qian Wang, and Xianghai Xiao, "A Modified Artificial Bee Colony Algorithm Based on Converge-Onlookers Approach for Global Optimization," *Applied Mathematics and Computation*, vol. 219, no. 20, pp. 10253-10262, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[30] He Huang, Min Zhu, and Jin Wang, "An Improved Artificial Bee Colony Algorithm Based On Special Division and Intellective Search," *Journal of Information Processing Systems*, vol. 15, no. 2, pp. 433-439, 2019. [CrossRef] [Google Scholar] [Publisher Link]