Intelligent Metaheuristic-based Handover Algorithm for Vehicular Ad hoc Networks

Gbenga O. Oladosu, Chunling Tu *, Pius A. Owolawi, and Topside E. Mathonsi

Department of Computer Systems Engineering, Pretoria, Tshwane University of Technology, South Africa;
Email: gbento003@yahoo.co.za (G.O.O.), DuC@tut.ac.za (C.L.T.), OwolawiPA@tut.ac.za (P.A.O.), MathonsiTE@tut.ac.za (T.E.M.)
*Correspondence: DuC@tut.ac.za(C.L.T.).

Abstract*—Recently, Vehicular Ad hoc Networks (VANETs) are becoming increasingly popular. VANETs are a subcategory of Mobile Ad hoc Networks (MANETs) in which nodes represent vehicles equipped with On-Board Units (OBUs). The fundamental reason is that VANETs improve safety for road users by providing vehicles with real-time road-related information. However, the increasing number of vehicles being introduced into these networks causes handover delays, and end-to-end delays, among other things. Therefore, the Quality of Service (QoS) is affected. This article proposes an Intelligent Metaheuristic-based Handover Algorithm (IMHA) to improve QoS in VANETs. The proposed IMHA is designed and implemented by integrating two of the most popular and recent optimization methods, namely disturbance Particle Swarm Optimization (d-PSO) and Ant Colony Optimization (ACO), wherein d-PSO assigns different priority levels to vehicles on the road to ensure safety meanwhile ACO determines the most profitable routes from the source to the destination. Furthermore, the Congestion Problem Reduction (CPR) algorithm is implemented in the IMHA to define the requests to process in priority order. The ACO and d-PSO hybrid methods have been tested and evaluated in real-world VANETs, giving us more confidence in their performance and robustness. Network Simulator 2 (NS-2) is used to simulate the proposed algorithm. Based on the outcomes, IHMA reduces end-to-end and handover delays and improves throughput at different vehicle velocities and network packet sizes. Consequently, this proposed solution guarantees improved QoS in VANETs. The experiment results show the proposed method outperforms existing handover algorithms, with a throughput of 92%, an end-to-end delay of 0.8 seconds, a handover delay and a computation time of less than 2.0 seconds, and an average memory usage of 60%.

***Keywords*—VANETs, optimization, Handover, ACO, d-PSO, QoS**

I. Introduction

In this digital age, the tsunami of digital technology tools and solutions has changed how the world's population exchanges and consumes essential information [1]. Vehicular Ad hoc Networks (VANETs) are imperative in ensuring better communication between drivers on the road. VANETs promote the exchange of road-related information without being restricted by time and place. This has led to a lot of research on facilitating communication between vehicles and the Internet. VANETs have a dynamic topology where each node can go about as a client or server and run routing algorithms in a distributed environment. VANETs mimic the behavior of Mobile Ad hoc Networks (MANETs) in which vehicle nodes can determine mobile or wireless communication [2].

VANETs, also known as Intelligent Transportation Networks (ITNs), play a vital role in Smart Transportation Systems (STSs). The research VANETs introduced to ensure road safety, passenger entertainment, and other related road services. Fatemidokht and Rafsanjani [3] characterized VANETs as a subcategory of MANETs; however, their architecture, testing capabilities, and applications differ. The research in [3, 4] also agreed that VANETs are a subset of MANETs where information can be transmitted between nearby vehicles and road infrastructure using Wireless Fidelity (Wi-Fi), ZigBee, Long-Term Evolution (LTE), and Visible Light Communications (VLC). Hence, one may presume that any VANET is a sub-form network made by applying the standards of MANETs to advance remote vehicle communication between vehicles in nearness. Therefore, these networks promote road safety and entertain users [3, 5]. Today, vehicles are equipped with sensors and specialized gadgets to send and receive essential and real-time information, for example, road conditions, traffic, and many more. VANETs support a wide range of applications. The research in [3] characterized two types of VANET applications: safety and comfort. Safety applications include collaborative traffic monitoring, destination route optimization, and collision avoidance [3]. On the other hand, comfort applications include weather forecasts, restaurants, gas stations, and hotel locations [3]. These applications include; electronic brake lights, platooning, traffic information systems, truck emergency services, and highway services. The qualities of these organizations incorporate self-association, dynamic attributes, and profoundly versatile nodes [3, 6].

Manuscript received July 19, 2022; revised October 24, 2022; accepted February 21, 2023.

The research in [3, 7–9] characterized two communication channels available in VANET, specifically, Vehicle-2-Vehicle (V2V) and Vehicle-2-Infrastructure (V2I). Generally, VANETs utilize IEEE 802.11p to locally uphold V2V and V2I communications using On-Board Units (OBUs) and Road-Side Units (RSUs), respectively. Vehicles use OBUs or even Application Units (AUs) for communication. RSUs transmit information to/from the Internet. Regularly, V2V depends on dedicated proximity communication channels; meanwhile, V2I depends on General Packet Radio Service (GPRS), Wireless Fidelity (Wi-Fi), or Worldwide Interoperability for Microwave Access (WiMAX) [10]. RSUs are Wireless Access Vehicular Environment (WAVE) devices located next to roads, such as an intersection or nearby parking spaces [3, 11]. Additionally, V2V maintains remote communication between vehicles in a direct and multi-hop manner; meanwhile, V2I maintains vehicle-to-RSU communications [5, 10], as shown in Fig. 1. These investigations employ both V2V and V2I to determine vehicle priority and establish the shortest route to the destination. The objective is to address the performance bottleneck and improve the QoS.

The advantages of VANETs include increased safety, effective traffic management, reduced road accidents, and further ensuring that travelers feel comfortable by facilitating valuable information exchange and rapid decision-making via the Internet [12]. In this manner, these networks can be considered innovations to promote security-related applications [10]. Therefore, the deployment of these networks is based on network connections [13, 14].

In recent years, advanced Internet of Things (IoT) devices and vehicles on roads have been increasing [3, 9, 13], resulting in more demand for VANET resources and services. However, the advanced vehicles can cause delays in handover and end-to-end communication, leading to problems such as congestion and poor Quality of Service (QoS) in VANETs [5].

Recently, nature-inspired metaheuristics and algorithms have been developed and widely adopted to tackle the abovementioned challenges. Despite their widespread use, these algorithms often suffer from unreliable performance, insufficient validation, overused comparisons, and immature usage and investigation procedures [15]. Meanwhile, most existing algorithms require high computational power, increasing nodes' energy consumption and reducing energy efficiency. On the other hand, some algorithms use the traditional carry-and-forward method when the next packet forwarder vehicle cannot be located. This method involves vehicles continuously sending data until they connect with another vehicle, which can cause data loss and delays. Furthermore, none of the existing algorithms includes a prioritization component. Prioritizing is crucial to ensure a certain level of performance during the handover and delivery processes.

Therefore, this paper proposes an Intelligent Metaheuristic-based Handover Algorithm (IMHA) to improve the QoS in VANETs. IMHA defines different vehicle priorities and restricts the number of vehicle requests to process at a time. The proposed algorithm integrates two advancement algorithms to be specific: disturbance Particle Swarm Optimization (d-PSO) and Ant Colony Optimization (ACO). The d-PSO is a dynamic optimization algorithm that can adjust the priority levels of vehicles in real time based on environmental changes. It can consider vehicle speed, direction, and type to ensure road safety and efficient road network use. This study uses d-PSO to provide different priority levels for every vehicle node in the network. However, d-PSO is a complex algorithm that requires a lot of computational resources to implement, and this can be a disadvantage in real-time systems where speed and efficiency are critical.

Conversely, ACO is a meta-heuristic algorithm that can find the optimal routes in a VANET based on traffic conditions, road conditions, and vehicle information. However, ACO may not consider real-time changes in the environment and may be unable to respond quickly to unexpected events such as accidents or road closures. It has been used to determine and make decisions on the most profitable path between the source and destination of each vehicle. This helps to eliminate significant long routes and thus reduce end-to-end delays. By combining the strengths of ACO and d-PSO, the hybrid method provides a more robust and dynamic solution for routing in a VANET. The ACO algorithm aids in providing optimal routes based on the available data. In contrast, the d-PSO algorithm aids in adjusting the priority levels in real-time to ensure road safety and efficient use of the road network. This results in improved road safety, routing efficiency, and a more dynamic and responsive system that can adapt to environmental changes and provides real-time vehicle updates. Furthermore, the research considered that it is not feasible to handle all vehicle requests simultaneously. To mitigate this, which contributes to congestion, we employed the Congestion Problem Reduction (CPR) algorithm to limit the number of vehicle requests to respond to at a time.

Some potential advantages of the proposed IMHA are:

- ACO and d-PSO can handle large-scale networks with many nodes, making them suitable for VANETs.
- These methods can adapt to network changes, making them suitable for VANETs where the network topology is constantly changing.
- These methods improve QoS by providing low end-to-end delay and high packet delivery ratio, making them suitable for VANETs requiring a low end-to-end delay and high packet delivery ratio.
- These methods have been tested and evaluated in real-world VANETs, giving more confidence in their performance and robustness than others.

The experiments comparing the proposed IMHA to the most advanced techniques have validated its effectiveness. This study used Network Simulator 2 (NS-2) to simulate and evaluate IMHA. The performance of IMHA was compared to the Adaptive Intersection Selection Mechanism (AISM), Efficient Geographical Source Routing (EGSR), and Chimp Optimization and Hunger

Games Search (ChOA-HGS) [6, 15, 16]. The results showed that IMHA outperformed the other techniques by reducing handover and end-to-end delays, improving throughput, and reducing computation time and memory usage.

The rest of the study is structured as follows. Section II analyzes related research. Section III examines the d-PSO and ACO algorithms. Section IV introduces the design and architecture of the system. Section V provides a discussion of the algorithm implementation and analyses the results. Finally, Section VI summarizes and discusses future improvements.

II. Related Works

In recent decades, much research has been conducted in the field of VANETs. Therefore, various algorithms have been proposed, designed, and implemented. However, previous research paid more attention to security, but the time delays and congestion issues were not well addressed.

Sasirekha *et al.* [2] introduced a heuristic method to reduce network overhead by eliminating the worst-performing node that transmits a copy of the message to the destination. In this research, ACO was used to ensure that routing is optimized. This leads to the correct selection of neighboring nodes. Route Mapping Ant Colony Optimization (RMAP-ACO) was proposed to ensure proper decision-making during route establishment and to adopt similar features by tracking local information and intermediate nodes. RMAP-ACO claims to reduce network overhead but does not reduce the message delivery rate. It also reduces data packet transmission delays within distributed networking environments. RMPACO also provides adaptive features and scalability in dense networks. Compared to other technologies, this model shows better compensation. However, their study found that recent studies have proposed evaluating model performance with machine learning algorithms.

Goswami *et al.* [4] proposed a clustering algorithm that works well on V2V communication. The proposed algorithm is a hybrid clustering mechanism called Genetic Algorithm-Ant Colony Optimization (GA-ACO) to enhance the lifetime and consistency of the network topology. The algorithm deals with the constant changing of VANET environments in terms of its topology. Experimental evaluations show that GA-ACO clustering technology performs much better than ACO, MOPSO, and CLPSO clustering algorithms regarding network stability and efficiency, reducing communication overhead. However, further investigation is proposed into more extensive networks. Meanwhile, system resources (memory and central processor time) are utilized the least, so further examination is suggested.

Fatemidokht and Rafsanjani [3] proposed and developed Fuzzy Ant Colony Optimization (FAnt) for fuzzy logic-based ACO theory in VANETs to maximize packet rate and minimize the end-to-end delay. This model was proposed depending on the features and applications of VANETs to ensure efficient routing. FAnt was considered in contrast to other protocols for routing, including Ad hoc On-Request Distance Vector (AODV), ACO, and more. The test assessment showed that FAnt produces an improved packet transfer rate, delay, throughput, routing overhead, and packet loss and thus performs better compared to other traditional algorithms. However, further assessment is proposed to improve the framework to support other QoS necessities (such as security and insurance) in highway scenarios.

Prakash *et al.* [9] proposed an intelligent adaptive route algorithm based on QoS for vehicles in Coimbatore. This algorithm uses ACO and AQRV optimization in VANETs. This is to achieve the best intelligent route and association between RSUs and vehicles. The algorithm adaptively selects the connections on each available node, and the data packets are released through these connections to reach the destination. The algorithm was expected to meet QoS prerequisites and the best QoS regarding network connectivity, probability, the delivery rate of packets, and end-to-end delay. The results showed that the likelihood of intelligent routes can be expanded. Tracking the best route around the city reduces travel expenses and deferrals. However, an idea was made for additional examination to track down the level of the metropolitan populace.

Mouhcine *et al.* [17] proposed another intelligent traffic routing and control framework, which can viably decrease and stay away from traffic congestion on the driver's route. The proposed procedure depends on the network architecture and is combined with the Distributed Ant Framework (DAS) algorithm. DAS shows better results during the search for the best and shortest routes. The whole framework depends on different innovations that make the interaction simple to handle and produce helpful outcomes. With this technique, road users can stay away from heavily congested routes. Exploratory assessments show that the recommended algorithm reduces traffic congestion by providing vehicles with information on routes with less traffic and thus reducing delays caused by waiting on traffic-congested routes. However, further exploration is suggested to implement a mobile application solution that users will use to drive and navigate.

Srivastava *et al.* [6] proposed an algorithm called the Adaptive Intersection Selection Mechanism (AISM) for VANETs, which utilizes ACO. AISM expressed that establishing a consistent route between two crossing points rather than a long route is considered an improved solution. This research claimed that when sending data packets, the best path within two convergences with a better network connection guarantees the sufficiency of the route. The test evaluation showed that, compared to other algorithms, AISM provides better results. However, the authors proposed an additional investigation on overhead control. Meanwhile, network clogs were also an issue for future exploration.

Gupta *et al.* [18] presented a new approach for efficient multi-hop clustering in VANETs using a prediction-based method and adaptive relay node selection. The proposed system used a prediction-based algorithm to select relay nodes expected to have good connectivity with other nodes in the network. This improved the clustering process's overall efficiency and reduced the number of control messages needed for cluster formation. The authors also presented an adaptive relay node selection algorithm that considers the node's mobility, remaining energy, and position to select the best relay node. This improved the overall performance of the multi-hop clustering process and increased the network's lifetime. Simulation results showed that the proposed approach outperforms existing methods regarding network lifetime and packet delivery ratio. However, the proposed system was evaluated for very large-scale networks, so it would be beneficial to test it in such scenarios to assess its scalability. In addition, the approach was not evaluated for its security and privacy features.

Mouhcine *et al.* [15] proposed a hybrid solution to tackle clustering and multi-hop routing optimization challenges in Underwater Wireless Sensor Networks (UWSNs). The method combines ChOA and HGS, Ant-Lion Optimization (ALO) Algorithm, and Neural Networks (NNs). Incorporating ChOA and HGS into a hybrid approach enhanced the node clustering process, while the ALO algorithm addressed optimization issues and sensor selection. ALO has been utilized for optimization problems in various fields, such as image compression, feature selection, and energy optimization in wireless sensor networks (WSNs); however, it may not be the most appropriate approach for optimization problems that involve a large number of variables, like those found in VANETs. Simulation results indicated that the proposed hybrid ChOA-HGS algorithm outperforms traditional ChOA and HGS algorithms regarding energy efficiency and network lifespan. However, its performance in large-scale networks remains untested and requires further evaluation. The method's focus on UWSNs limits its generalizability and potential applications to other network types, such as VANETs. Moreover, its security and privacy evaluations are also a concern. Additionally, the convergence time of ChOA-HGS to a good solution may be prolonged, which can be an issue in time-sensitive applications. Finally, its susceptibility to noise and disturbances may also limit its ability to find optimal solutions in certain scenarios.

III. Overview of Particle Swarm Optimization and Ant Colony Optimization Algorithms

This research incorporates d-PSO and ACO to curb the different research gaps encountered in the existing QoS and VANET handover algorithms.

A. Disturbance Particle Swarm Optimization (d-PSO)

PSO was generally proposed to optimize continuous nonlinear functions [19–21]. This stochastic algorithm mimics the navigation and forging of a school of fish, a flock of birds, and more. In this algorithm, each solution to the problem is treated as a particle [19]. Navigation and forging include cohesion to ensure that particles can conjoin, separation to prevent them from coming too close to each other, and alignment to ensure that each particle follows the swarm [14]. The objective is to imitate an arbitrary pursuit in the solution space to obtain the most extreme value of the target [19]. This study employs a modified PSO known as disturbance PSO (d-PSO). It is an optimization algorithm that is based on the traditional PSO algorithm but with the addition of a disturbance term. Using a disturbance term in the algorithm allows the particles to expand their search space more extensively, improving their ability to find global solutions. This helps prevent particles from getting stuck in local optima, reducing the likelihood of premature convergence. Additionally, the disturbance term enables the particles to adapt to changing parameters of the optimization problem, making d-PSO suitable for problems with dynamic conditions. However, this algorithm may require fine-tuning parameters to achieve the optimal solution, which can be time-consuming and may not always result in the best solution for VANETs.

B. Ant Colony Optimization (ACO)

ACO simulates the cooperation of how ants behave in real-time, looking for a profitable route between two points [22]. Naturally, ants leave a synthetic substance called a pheromone to mark the path between the colony and the food source [21–23]. Therefore, the others could follow the trail of the deposited pheromone. The route of higher concentrations of pheromone attracts more ants [19]. The ACO performs random route searches and converges these searches to a more efficient path [20] to reduce delay and collision problems. It can run consistently and continuously adjust to changes to improve the QoS of network routing. However, ACO may require a high computational power, which can result in increased energy consumption and reduced battery life for nodes in VANETs.

IV. System Design and Architecture

This section discusses the architectural design and introduces the integration of d-PSO and ACO in the proposed IMHA. Furthermore, it analyzes various system components and configurations to optimize QoS during the VANETs handover processes.

A. System Architecture

Fig. 1 shows the proposed VANET composed of RSUs and OBUs. These nodes communicate freely in the network, whereby each vehicle node is identified by its assigned address. The algorithm runs at the distribution layer to promote prioritization and ensure a fair distribution of available network resources and services.

The proposed network architecture displays a distribution plan for vehicles to communicate and exchange critical information. It comprises three main parts: communicating vehicle nodes, OBUs, and RSUs. The vehicle nodes have OBUs for communication with RSUs. The OBUs are the primary communication device, providing the necessary processing power and memory for routing and data dissemination. RSUs are positioned along the roads to assist the vehicle nodes. To guarantee efficient communication, the IMHA hybrid algorithm of ACO and disturbance PSO operates at the distribution level. The ACO part finds cost-effective paths for vehicles; meanwhile, the PSO part prioritizes vehicles based on factors like speed. Another algorithm called CPR is used to control the number of requests from vehicles to ensure efficient processing. Communication between the vehicle nodes and RSUs is through wireless technologies like Wi-Fi, ZigBee, or LTE, and communication between the RSUs and network infrastructure is through wired connections like Ethernet or 3G/4G cellular networks. The architecture is adaptable to support changes in the network and has mechanisms for fault tolerance and network recovery for reliability.

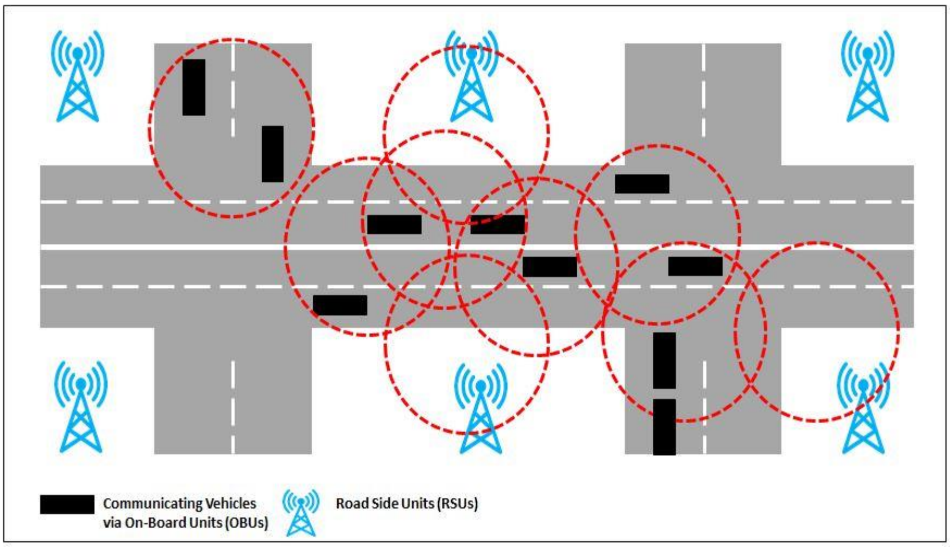

Figure 1. Proposed network distribution scenario.

B. System Model

The IMHA assimilates two popular techniques in the optimization environment, the traditional PSO modified in [17] and ACO proposed in [18]. Furthermore, the CPR algorithm is implemented to define limits regarding the number of vehicle demands to process in the order of priority at a given time. This is to guarantee QoS and save time and resource requirements.

In the network, we assume that there are n communicating vehicles. The position of each vehicle is represented by (x_i, y_i). To optimize the distribution of n vehicles, each solution (particle) can be defined as $(x_1, y_1, x_2, y_2, \ldots x_n, y_n)$. This means the particle is $2n$-dimensional for n vehicles. On the other hand, the velocity is calculated using Eq. (1).

$$v_{id}(t+1) = c_0 \times rand_n() + c_1 \times rand() \times (p_{ibest} - x_{id}) + c_2 \times rand() \times (p_{gbest} - x_{id}) \tag{1}$$

where c_0 represents the amplitude of the disturbance. This model sets c_1 and c_2 to 1, and c0 to the number of sensors, sensing range, and space. The p_{ibest} represents the best position ever found for each i-th particle and p_{gbest} represents the global best position. The $rand()$ represents random numbers between 0 and 1 independently. Meanwhile, the formula $rand_n$ is a standard normal distribution with an average zero and the unit standard deviation. This unique feature lowers the risk of local optimization, as in the traditional PSO algorithm. This is because the best position and global best solution may be in a suboptimal position. The disturbance allows the particle to jump away from the local optimal position.

On the other hand, IMHA ensures that each vehicle can send and receive messages to/from other vehicles through Eq. (2):

$$m_{\mathrm{n}} \in v \tag{2}$$

where m represents each vehicle n being part of vehicles v communicating to share valuable information on the road. This information includes traffic and more.

On the other hand, each vehicle can communicate with the nearest RSU, t, to establish the shortest route to the next RSU. This is achieved by ACO as shown in Eq. (3):

$$P_{t_1 t_n}^{(r)} = \begin{cases} \dfrac{\tau_{t_1 t_n}^{\propto}}{\sum_{t_n \in N_{t_1}^{(r)}} \tau_{t_1 t_n}^{\propto}} \; if \; t_n \in N_{t_1}^{(r)} \\ 0 \; if \; t_n \nexists N_{t_1}^{(r)} \end{cases} \tag{3}$$

where vehicle v, located anywhere, communicates with the nearest RSU, t_1, and uses the pheromone trail $\tau_{t_1 t_n}^{\propto}$ to calculate the probability, defined by P, to choose t_n as its next RSU. $\propto$ is the degree defined to represent the importance of the identified pheromones. $N_{t_1}^{(r)}$ represents sets of adjacent RSUs close to RSU t_1. The neighborhood of RSU t_1 has information about other RSUs to communicate with RSU t_1 besides its predecessor RSU. This ensures that a vehicle does not return to the RSU that has been visited. Every vehicle communicates with its RSU to the next, in close proximity, to find the most profitable route from its place of departure and destination. ACO ensures that the n_{th} ants' deposit $\Delta\tau^r$ of pheromone on the visited arcs of the RSU. The pheromone value $\tau_{t_1 t_n}$ on the visited arc (t_1, t_n) is updated as shown in Eq. (4):

$$\tau_{t_1 t_n} \leftarrow \tau_{t_1 t_n} + \Delta\tau^{(r)} \tag{4}$$

The probability of the arc being visited by the vehicles increases. This is because of the increasing pheromone. However, as vehicles move to the next RSUs to search for the shortest routes, the pheromones evaporate based on the relation of the arcs, as shown in Eq. (5):

$$\tau_{t_1 t_n} \leftarrow (1-p)\tau_{t_1 t_n};\ \forall(t_1, t_n) \in A \tag{5}$$

where $p \in (0,1)$ and A represent the arcs visited by any vehicle v to identify the cost-effective path from its origin to its destination. The increase in the intensity of the pheromone reduces delays as it helps vehicles not to take long paths toward their destination and, thus, improves path selection. Therefore, this iteration becomes a complete cycle that involves the movement of vehicles, evaporation, and pheromone deposits. This means that the pheromone information is updated as the vehicle reaches its destination, as shown in Eq. (6):

$$\tau_{t_1 t_n} = (1-p)\tau_{t_1 t_n} + \sum_{r=1}^{N} \Delta\tau_{t_1 t_n}^{(r)} \tag{6}$$

where $p \in (0,1)$ is defined as the pheromone decay factor. Meanwhile $\Delta\tau_{t_1 t_n}^{(r)}$ calculates the density of pheromones deposited on the arc on RSU $t_1 t_n$ by the best node. Naturally, the pheromone is constantly updated to increase the value that is associated with what is identified as the most profitable routes. The pheromone on the arc $t_1 t_n$ by the best nodes is calculated as shown in Eq. (7):

$$\Delta\tau_{t_1 t_n}^{(r)} = \frac{Q}{L_r} \tag{7}$$

where Q represents constant, and L_r represents the distance each vehicle travels to the destination.

Finally, the IMHA defines limits in terms of the number of vehicles that can communicate with one another simultaneously to address congestion problems. The CPR algorithm aids in this by defining the number of vehicle nodes to communicate with each other or RSUs. Therefore, at most, for example, only ten vehicles can communicate with each other. This is done in the order of priority.

Algorithm 1 Congestion Problem Reduction (CPR)

```
INPUT: Number of vehicle requests
OUTPUT:
DO WHILE number of requests > 0
    IF the number of requests > 10 THEN
        DO
            Process these requests in priority order.
            Once these requests have been processed, proceed to
            the other vehicle's request.
        LOOP UNTIL number of requests < 11
    ELSE
        Process these requests in priority order.
        Until every vehicle's request is processed
    END IF
LOOP
```

As mentioned above, the CPR algorithm ensures that a predefined number of vehicle demands are processed at a given time in an orderly manner. This process is repeated to process all demands. The goal is to reduce message congestion and processing delays. Limiting the number of requests by each vehicle makes the system more scalable, making it suitable for large-scale VANETs. Also, limiting the number of requests by each vehicle reduces congestion, making the network more reliable and efficient.

V. Implementation of Intelligent Metaheuristic-Based Handover Algorithm

This section discusses the implementation of IMHA. We also discuss and analyze the simulation results. Performance metrics, including throughput, end-to-end, handover delay, computation time, and memory usage, are considered in the simulation because these metrics significantly affect QoS during handover processes in VANETs.

A. Evaluation Metrics

- Throughput – measures the transmission between two nodes at a given time.
- End-to-end Delay – measures how long the data takes to reach the destination.
- Handover delay – measures the time required for continuous connections between providers.
- Computation time – measures how long it takes to perform a computation process or task.
- Memory usage - measures how much data is stored on or transferred from a device.

B. Simulation Environment

NS-2 Version 2.35 (NS-2.35) was used to conduct the simulations and generate network traffic mobility deployed on Windows (OSs). The simulation topology is illustrated as shown in Fig.2. It comprises 20 RSUs and 100 vehicles. The IMHA was deployed at the distribution layer of the network. The simulation was performed 20 times to provide accurate results. The simulation time was 300 s. The NS-2 results are analyzed based on throughput, end-to-end, handover delays, computation time, and memory usage. The proposed IMHA was evaluated and compared with AISM, EGSR, and ChOA-HGS.

Table I shows the parameters and values used during the simulations.

TABLE I: Simulation Parameters

Parameter	Value
Communication Range	300 m
Medium Access Control (MAC)	IEEE 802.11p
Simulation Time	300 seconds
Vehicle Speed	10 – 100 Km/h
Propagation Model	TwoRayGround
Queue Type	Queue/DropTail/PriQueue
Data Packet Size	1 – 6 Mb/s
Simulation Area	1800m x 840m

Network Animator (NAM) is a tool for visualizing and analyzing network traffic. It is used to view the flow of packets between devices on a network and can help with troubleshooting, performance analysis, and security investigations. It displays information such as the source and destination of packets, the type of packet, and the size of the packet. Fig. 2 shows the NAM created to simulate the network used in this work.

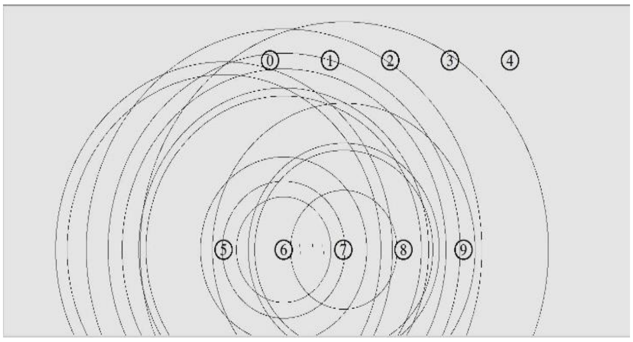

Figure 2. Simulation scenario.

C. Results and Analysis

This section compares the results of the IMHA algorithm with AISM, EGSR, and ChOA-HGS to assess its performance. AISM and EGSR are similar in traffic scenarios and aim to improve network throughput, end-to-end delay, handover delays, computation time, and memory usage. However, as seen in Fig. 3, all three algorithms, including AISM, EGSR, and ChOA-HGS, experience a decline in packet delivery rate due to the increase in routing control overhead in dynamic VANETs where nodes frequently move in and out of range. This leads to substantial routing overhead, slower communication, and increased delays in large-scale VANETs, where fast communication is critical.

AISM and EGSR use geographic information for routing, which may cause increased communication latency and be unsuitable for low-latency applications such as real-time safety alerts or navigation updates. Additionally, these algorithms are vulnerable to security threats like eavesdropping, tampering, and spoofing, requiring robust security measures.

On the other hand, ChOA-HGS has limited scalability due to its centralized approach, making it difficult to handle large networks and resulting in increased latency and decreased overall performance in large-scale VANETs. The central node in ChOA-HGS is a single point of failure, making it a security and privacy concern.

Moreover, none of these algorithms considered prioritizing vehicles during handover and delivery, leading to poor Quality of Service (QoS).

Despite its advantages, the ACO algorithm has a significant disadvantage where its convergence speed decreases as the number of iterations increases [24]. Furthermore, it has trouble with negative numbers and can get stuck in a stagnant phase. This issue is particularly pronounced in small cities with more ants. The algorithm also relies on local information sharing among vehicles, which can lead to suboptimal solutions if global information is unavailable. Additionally, it does not consider essential objectives such as security and privacy in VANETs. The d-PSO may also not be suitable for certain prioritization problems involving non-differentiable or non-continuous objective functions and relies on local information sharing, resulting in suboptimal solutions without global information. Hence, it is essential to consider alternative algorithms, such as the African Buffalo Algorithm (ABA) and others, for future work. However, like any optimization algorithm, the ABA has its drawbacks and should be carefully considered before using it in practical situations. The ABA has only been developed and evaluated for a limited number of optimization issues, and its effectiveness for other problem types is uncertain.

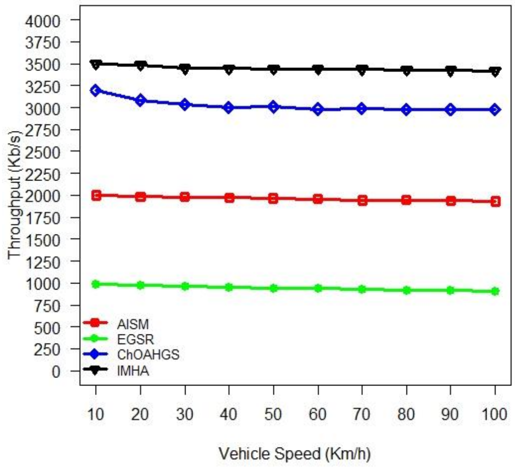

Figure 3. Throughput.

Throughput refers to the rate at which data is transmitted between two nodes at a specific time. The proposed IMHA method improves the average throughput, as demonstrated in Fig. 3. The proposed algorithm improves throughput by reducing routing overhead and prioritizing network communication. By combining the shortest route-finding capabilities of ACO with the disturbance-handling capabilities of PSO, the hybrid algorithm can find and maintain efficient communication routes between vehicles quickly. This results in less time spent retransmitting lost or corrupted packets, increasing overall network efficiency and improving throughput. The proposed CPR algorithm limits the number of vehicle demands processed over time, reducing processing delays and ensuring that high traffic loads do not impact the network performance. In addition, the hybrid algorithm can adapt to changes in the network conditions more quickly and efficiently than AISM, EGSR, and ChOA-HGS. This results in fewer delays in communication and improved overall network performance, further contributing to increased throughput. In conclusion, IMHA improves the efficiency and reliability of communication and ensures a high level of QoS for the VANETs, leading to improved throughput compared to AISM, EGSR, and ChOA-HGS.

The end-to-end delay measures the duration for the data to arrive at its final destination. The results in Fig. 4 indicate that the proposed IMHA method has significantly reduced end-to-end latency compared to AISM, EGSR, and ChOA-HGS algorithms. The proposed algorithm improves end-to-end delay by combining the benefits of different algorithms to address routing and prioritization in VANETs. The ACO algorithm helps find the shortest route, reducing the distance data needs to travel and reducing end-to-end delay. The d-PSO helps prioritize the requests, ensuring that the most important requests are addressed first, reducing the delay caused by unimportant requests.

Limiting the number of requests by each vehicle using CPR reduces congestion, making the network more reliable and efficient and reducing end-to-end delay. Additionally, the proposed approach can be designed to handle failures and disruptions, making the network more reliable and reducing the delay caused by network disruptions. In conclusion, IMHA improves end-to-end delay by reducing delays caused by congestion, network disruptions, and unimportant requests.

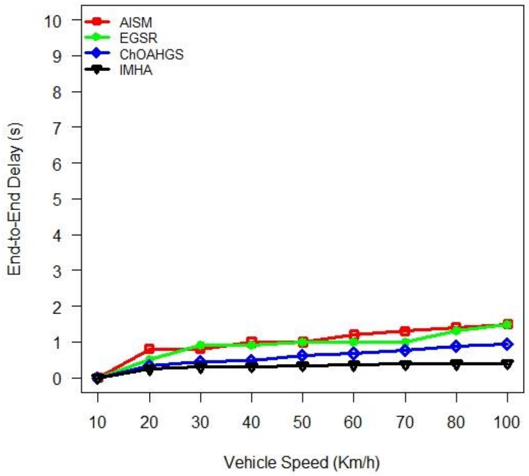

Figure 4. End-to-end delay.

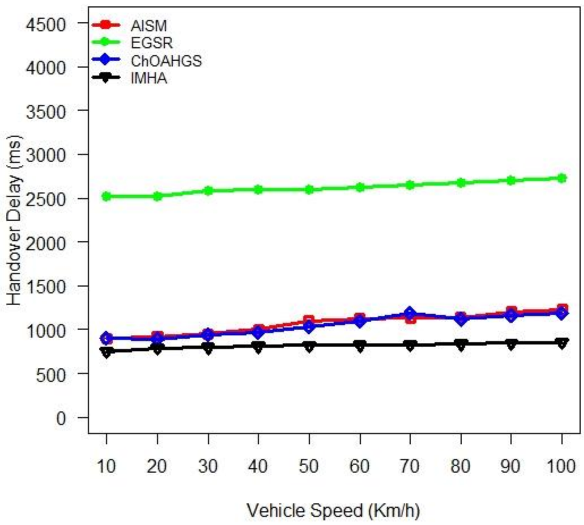

Figure 5. Handover delay.

The handover delay measures the time necessary for uninterrupted connections during transitioning from one service provider to another. Fig. 5 shows that IMHA outperforms AISM, EGSR, and ChOA-HGS algorithms in terms of reducing handover delays. The proposed algorithm significantly improves handover delay in VANETs. The ACO algorithm helps find the shortest route between the source and the destination, reducing the time it takes for a vehicle to move from one network to another. The d-PSO algorithm, on the other hand, prioritizes the requests, ensuring that the most important ones are addressed first. By prioritizing the requests, the handover process becomes smoother and more efficient, reducing the delay. Additionally, the algorithm uses CPR to limit the number of requests by each vehicle which helps reduce congestion, making the network more reliable and efficient. The reduced congestion also minimizes the handover delay as fewer requests are processed simultaneously, allowing the vehicles to switch between networks more quickly. In conclusion, IMHA provides a more optimized solution, reducing handover delay and ensuring a more seamless user experience.

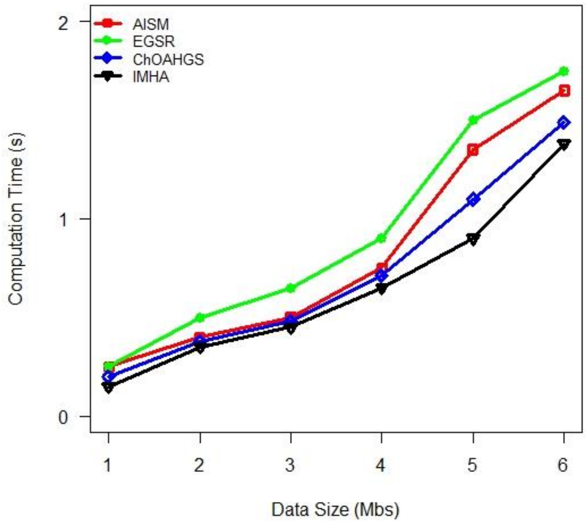

Figure 6. Computation time.

The computation time measures the duration required for a computational operation or assignment. Fig. 6 illustrates that the proposed IMHA decreases the computation compared to AISM, EGSR, and ChOA-HGS algorithms. The proposed algorithm improves computation time by leveraging the strengths of ACO, d-PSO, and CPR algorithms. As mentioned previously, the ACO algorithm uses a swarm intelligence approach to find the shortest route, reducing the time to find a solution. The d-PSO algorithm, on the other hand, uses particle swarm optimization to prioritize the requests, reducing the time taken to make decisions. By combining these algorithms, the system is able to find solutions faster and more efficiently, reducing computation time. Additionally, by limiting the number of requests by each vehicle, the system reduces congestion, reducing the time to process requests. Furthermore, using this approach, the system can be optimized for performance, reducing the time to find solutions and making it more cost-effective. All these factors combined contribute to a significant improvement in computation time.

Memory usage, however, measures the data stored or moved from a device. Fig. 7 illustrates that the IMHA approach reduces memory usage compared to AISM, EGSR, and ChOA-HGS algorithms. The proposed algorithm helps to improve memory usage in VANETs by using the strengths of different algorithms. This hybrid approach helps reduce the memory footprint by limiting the amount of stored and processed data. The ACO algorithm is designed to find the shortest route with minimum memory usage. On the other hand, the d-PSO prioritizes the requests to minimize the amount of data stored in memory. Additionally, the CPR algorithm to limit the number of requests by vehicles helps to reduce the amount of data stored in memory by restricting the number of requests processed. By combining these different algorithms, this hybrid system provides a more efficient and optimized solution for memory usage in VANETs. This helps conserve memory resources and improve the network's overall performance.

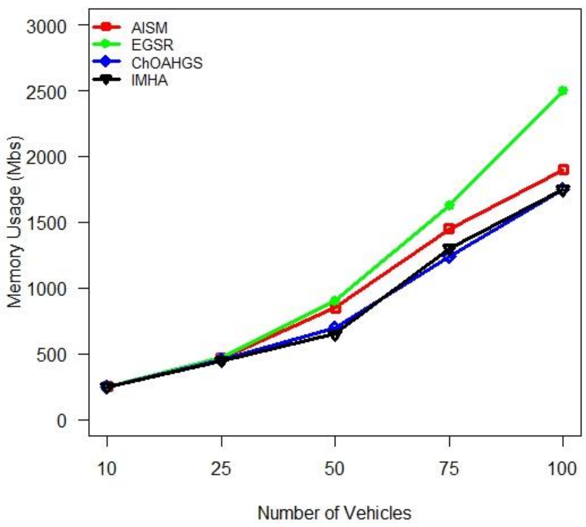

Figure 7. Memory usage.

D. Sensitivity Analysis of IMHA

The objective of this section is to examine the responsiveness of the IMHA to various parameter values. The aim was to evaluate the efficiency of the proposed hybrid algorithm to identify the ideal parameters for optimal outcomes. The algorithm was run for several iterations with stopping criteria of 10% error.

- The ACO parameters were tested by varying the number of ants from 10 to 100, and the results were analyzed. It was discovered that a higher number of ants led to improved performance but also resulted in a higher computational cost. The optimal number was found to be 30. The pheromone decay rate was also varied from 0.1 to 0.9 and analyzed, with a rate of 0.5 being determined as the best option. Finally, the pheromone update rule was changed between global and local, and the results were evaluated.
- The parameters for the d-PSO algorithm were examined by changing the population size from 20 to 100. The results showed that increasing the population size enhanced the algorithm's performance but also increased the computational cost. The optimal population size was found to be 40. The number of particles was also adjusted from 10 to 50 and analyzed. The findings revealed that more particles improved the algorithm's performance but came at an increased computational cost. The optimal number of particles was determined to be 30. The velocity was tested from 10 to 100, which showed that the best results were achieved with an initial velocity 10.
- The problem size was determined by the variation in the number of nodes and edges, ranging from 10 to 50. The findings indicated that as the number of nodes and edges increased, the algorithm's performance improved, leading to a rise in computational cost.
- The objective function was altered to prioritize the shortest distance for each vehicle. Still, the results indicated that the original objective function, which was focused on the total distance traveled by all vehicles, produced the best results.
- The stopping criteria varied from 5% error to 10% error, and the outcome indicated that the best results were obtained with stopping criteria of 10% error.

VI. CONCLUSIONS

In this study, the authors proposed, designed, and implemented IMHA, a new approach to improving the QoS performance in VANETs. This was achieved by integrating ACO and d-PSO algorithms. The aim was to tackle performance bottlenecks related to handover delays, end-to-end delays, throughput, computation time, and memory usage. The ACO algorithm was used to determine the most efficient route between the source and destination for each vehicle on the road; meanwhile, d-PSO was employed to prioritize vehicles for road safety. In addition, the authors also implemented a CPR algorithm to process vehicle demands in priority order and prevent congestion problems.

Experimental evaluations using NS-2 simulations showed that IMHA outperforms existing approaches, such as AISM, EGSR, and ChOA-HGS. With a throughput of 92%, an end-to-end delay of 0.8 seconds, a handover delay and computation time of less than 2.0 milliseconds, and an average memory usage of 60%, IMHA demonstrates significant improvements in QoS performance.

In conclusion, the proposed IMHA algorithm improved routing efficiency, road safety, system responsiveness, and low end-to-end delay and high packet delivery ratio, making it suitable for VANETs requiring a low end-to-end delay and high packet delivery ratio. The authors suggest that future research should focus on the algorithm's security, given the increasing reliance on the Internet of Things (IoT) and the widespread adoption of modern MAC protocols, such as 802.11ac or the latest 802.11ax.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

G. O. Oladosu wrote the entire paper, including an analysis of data and simulation. Chunling Tu contributed to supervision, proofreading the paper, and correcting the contents and structure. P. A. Owolawi and T. E. Mathonsi provided valuable comments, co-supervision, and all authors approved the final version of the paper.

ACKNOWLEDGEMENT

The researchers thank the Tshwane University of Technology for their support.

REFERENCES

[1] L. A. Saxon, "Mobile health application solutions," *Circulation: Arrhythmia and Electrophysiology*, vol. 9, pp. e002477, February 2016.

[2] S. Sasirekha, P. Amudhavalli, and P. Sherubha, "Efficient route map-based ant colony optimization for route discovery in VANET," in *Proc. 2019 International Conference on Communication and Signal Processing (ICCSP)*, 2019, pp. 0455–0459.

[3] H. Fatemidokht and M. K. Rafsanjani, "F-Ant: An effective routing protocol for ant colony optimization based on fuzzy logic in vehicular ad hoc networks," *Neural Computing and Applications*, vol. 29, pp. 1127–1137, 2018.

[4] V. Goswami, S. Verma, and V. Singh, "A novel hybrid GA-ACO based clustering algorithm for VANET," in *Proc. 2017 3rd International Conference on Advances in Computing, Communication & Automation (ICACCA)(Fall)*, 2017, pp. 1–6.

[5] S. Lakshmanaprabu, K. Shankar, S. S. Rani *et al.*, "An effect of big data technology with ant colony optimization based routing in vehicular ad hoc networks: Towards smart cities," *Journal of Cleaner Production*, vol. 217, pp. 584–593, 2019.

[6] A. Srivastava, A. Prakash, and R. Tripathi, "An adaptive intersection selection mechanism using ant Colony optimization for efficient data dissemination in urban VANET," *Peer-to-Peer Networking and Applications*, vol. 13, pp. 1375–-1393, 2020.

[7] S. S. Salihin, L. A. Nissirat, R. M. Noor, and I. Ahmedy, "Handover schemes for vehicular ad-hoc networks over long term evolution advanced: A survey," in *Proc. 2018 International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA)*, 2018, pp. 1–7.

[8] N. Melaouene and R. Romadi, "An enhanced routing algorithm using ant colony optimization and VANET infrastructure," in *Proc. MATEC Web of Conferences*, 2019, p. 02009.

[9] J. Prakash, N. Sengottaiyan, and S. H. Nandhini, "Smart routing for Vehicle at optimal position with ant colony optimization and AQRV in VANET," *EAI Endorsed Transactions on Energy Web*, vol. 5, p. 155566, 2018.

[10] F. Azzali, O. Ghazali, and M. H. Omar, "Performance analysis of vertical handover in vehicular ad-hoc network using media independent handover services," *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, vol. 9, pp. 13–18, 2017.

[11] S. Al-Sultan, M. M. Al-Doori, A. H. Al-Bayatti, and H. Zedan, "A comprehensive survey on vehicular ad hoc network," *Journal of network and computer applications*, vol. 37, pp. 380–392, 2014.

[12] T. Qiu, X. Wang, C. Chen, M. Atiquzzaman, and L. Liu, "TMED: A spider-Web-like transmission mechanism for emergency data in vehicular ad hoc networks," *IEEE Transactions on Vehicular Technology*, vol. 67, pp. 8682–8694, 2018.

[13] H. Al-Raweshidy, *Traffic-aware VANETs Routing for City Environments-A Protocol Based on Ant Colony Optimization*, 2017.

[14] G. Oladosu, C. Du, and P. A. Owolawi, "Optimized handover algorithm for vehicular ad hoc network," in *Proc. the 2019 7th International Conference on Information Technology: IoT and Smart City*, 2019, pp. 317–321.

[15] Y. Yang, Y. Wu, H. Yuan, M. Khishe, and M. Mohammadi, "Nodes clustering and multi-hop routing protocol optimization using hybrid chimp optimization and hunger games search algorithms for sustainable energy efficient underwater wireless sensor networks," *Sustainable Computing: Informatics and Systems*, vol. 35, pp. 100731, 2022.

[16] F. Goudarzi, H. Asgari, and H. S. Al-Raweshidy, "Traffic-aware VANET routing for city environments – A protocol based on ant colony optimization," *IEEE Systems Journal*, vol. 13, pp. 571–581.

[17] E. Mouhcine, K. Mansouri, and Y. Mohamed, "Solving traffic routing system using VANET strategy combined with a distributed swarm intelligence optimization," *J. Comput. Sci*, vol. 14, pp. 1499–1511, 2018.

[18] S.A. Rashid, L. Audah, M. M. Hamdi, and S. Alani, "Prediction based efficient multi-hop clustering approach with adaptive relay node selection for VANET," *Journal of Communications*, vol. 15, pp.332–344, 2020.

[19] S. Ding, C. Chen, J Chen, and B. Xin, "An improved particle swarm optimization deployment for wireless sensor networks," *Journal of Advanced Computational Intelligence and Intelligent Informatics*, vol. 18, pp. 107–112.

[20] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *Proc. the Sixth International Symposium on Micro Machine and Human Science*, 1995, pp. 39–43.

[21] A. Gupta and S. Srivastava, "Comparative analysis of ant colony and particle swarm optimization algorithms for distance optimization," *Procedia Computer Science*, vol. 173, pp. 245–253, 2020.

[22] M. Dorigo and T. Stützle, "Ant colony optimization: overview and recent advances," *Handbook of metaheuristics*, pp. 311–351, 2019.

[23] V. Shruthi and S. Hemanth, "Simulation of ACO technique using NS2 simulator," *Int J Eng Trends Technol*, vol. 23, pp. 403–406, 2015.

[24] M. Mulani and V. L. Desai, "Design and implementation issues in ant colony optimization," *International Journal of Applied Engineering Research*, vol. 16, pp. 1–11, 2018.