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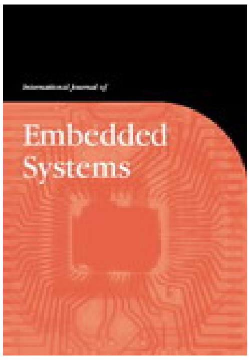

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Optimising routing using nature inspired grasshopper algorithm to improve performance of VANETs

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Abstract: The paper integrates grasshopper algorithm as a bio-inspired method to improve the performance of vehicle ad hoc networks (VANETs). VANETs are highly mobile with quick topology changes and limited communication range, with a large network architecture supported by roadside units (RSUs). Thus, the need for customised routing strategies inspires the work to present modified pairing and evaluation behaviour. A unique decision-making mechanism within the grasshopper algorithm is designed and implemented. A fitness function is introduced that takes into account energy efficiency and delay for the broadcast response to evaluate the total cost including execution and idle time. The reduction of packet transmission delay forms the primary goal. The quality of service (QoS) parameters are evaluated against state-of-art algorithms to depict its significance in addressing the current challenges. The research focuses on the application of an advanced fitness function as essential elements in VANET performance optimisation using the grasshopper algorithm.

Keywords: vehicular ad hoc network; road side units; quality of service; QoS; grasshopper algorithm; fitness function.

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1 Introduction

The vehicular ad hoc network (VANET) consists of automobiles that can establish connections among themselves using either a vehicle-to-vehicle (V2V) communication network or a vehicle-to-roadside unit (RSU) communication network (Al-Shalthry and Al-Dubai, 2019). Roadside units are small set of units that are placed on the sides of the roads based on the communication strength of the RSU. Deployment and assignment of RSU is both hardware and software oriented and hence the communication cost of V2RSU communication is higher. To reduce the overall cost of investment (CoI), V2V communication has gained a lot of attention in the last couple of years (Zhang et al., 2019b). Due to high mobility factor in VANET, traditional approaches fail to deliver quality of service (QoS) in the most proficient way as compared to mobile ad hoc networks (MANET) (Aziz and Al-Otaibi, 2018). Design of efficient routing strategy may lead to optimised QoS. We find broadcast-oriented routing algorithms like the ad hoc on-demand distance vector (AODV) routing protocol since the typical routing strategy used in VANET has been adapted from MANET (Devi and Kannammal, 2016). In addition to the existing base architecture of grasshoppers, the proposed work has tuned the pairing and evaluation behaviour of the grasshopper based on the proposed case scenario.

1.1 AODV

A well-liked routing protocol used in VANETs is AODV. A VANET is a sort of MANET that uses RSUs as network infrastructure and vehicles as nodes (Fekair et al., 2019). The unique characteristics of VANETs, such as high mobility, fast topology changes, and limited communication range, require special routing protocols that can handle these challenges effectively.

- High mobility: The VANET vehicles are always moving and therefore the network topology is extremely dynamic. Vehicles also move quickly, which makes it difficult to maintain reliable communication links and necessitates adaptive routing algorithms that can react fast to changes in the network topology.
- Fast topology change: The mobility of vehicles causes VANETs' topology to shift quickly and unpredictably. Therefore, the routing protocols need to be flexible and responsive in order to adapt to the rapidly shifting topology.
- Limited communication range: In VANETs, the communication range is restricted to usually a few hundred metres. The practical limitations of vehicle communication systems, such as dedicated short range communications (DSRC), are the cause of this restricted range. Vehicles can only speak directly to people who are nearby as a result.

Reactive routing protocols like AODV only create routes when they are necessary. In order to find routes in between the starting and ending nodes, it employs the broadcast technique (Cahyadi and Hwang, 2022). The basic idea behind AODV is to maintain a route table at each node that stores the next- hop information for all known destinations. A node initially checks its route database to determine if it has a proper route before sending data to a destination. If it doesn't, a route discovery procedure is started. AODV consists of three main steps: route discovery, route maintenance, and route error handling.

1.1.1 Route finding

A source node initially checks its route database to see if it has a valid route before sending data to a destination node. It broadcasts a route request (RREQ) packet to its neighbours if it does not. The IP addresses of the source node, the destination node, a special number for the sequence, and the source node's present sequence number for the target are all included in the RREQ packet (Ma et al., 2020). Unless it has already seen this RREQ (found by looking at the sequence number), every node that receive the RREQ packet modifies its own route table before broadcasting the RREQ to its neighbours. A route reply (RREP) packet is sent back to the source node when the RREQ arrives the node that is the destination or an intermediate node with a new path to the destination. The IP address of the source node, the sequence number of the destination node, the hop count, and the estimated time of arrival (ETA) of the data at the destination node are all included in the RREP packet. The reverse path is used to return the RREP to the source node.

1.1.2 Route maintenance

AODV periodically checks the current state of the routes via HELLO messages. A node sends a route error (RERR) packet if it waits a specific amount of time after not receiving a HELLO message from its next-hop node before concluding that the link is broken. The RERR packet is broadcast to all nodes that are using the broken link, so that they can update their route tables and find alternative routes (Cai et al., 2022).

1.1.3 Route error handling

AODV also handles route errors by sending RERR packets. The RERR packet contains the IP address of the unreachable destination node. Nodes that receive the RERR packet update their route tables and remove the broken link from their routes. Suppose there are five nodes in a VANET, G, H, I, J, and K. Node G wants to send data to node K. Node G first checks its route table and finds that it does not have a valid route to node K. It then initiates a route discovery process by broadcasting a RREQ packet to its neighbours. The RREQ packet reaches node B, which updates its route table and then broadcasts the RREQ to its neighbours. Node B sends the RREQ to node C, AODV is a reactive routing protocol and chooses the path in V2V communication based on the current distances that is measured using equation (1) as follows.

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + +\left(y_i - y_j\right)^2} \tag{1}$$

where 'I' and 'j' are vehicles and i, j is $\{1, 2 \ldots \ldots n\}$ and n is not equal to infinity, where n is the number of vehicles in the simulation list. x, y are the geometric 2d locations of the vehicles. As the vehicles are mobile in nature, the vehicle might travel a certain distance from the time it responds to the RREQ that is transferred by the source vehicle (S_p) to the time it actually gets the chance to route the packet. In order to find the current location of the respondent vehicle' 'j', the source vehicle i uses a location prediction algorithm (LPA) to calculate the actual location of the respondent vehicle. When the source vehicle broadcasts the 'hello packet' as illustrated in AODV, the nearby vehicles that are part of the network, responds back to seeker with three-bit information. The first bit illustrates the speed of the respondent, the second bit illustrates the direction of the movement and the third bit represents the overall computation time in order to transfer the data that is generated by the source vehicle. LPA calculates the approximate distance of the respondent by using equation (2) as follows.

$$d_j^t = \frac{S_j}{t_0 - t_1} \quad (2)$$

where S_j is the speed of the respondent, t_0 is the time when the route reply (*R-REP$_{ij}$*) has been received against the route request (*R-REQ$_{ij}$*) and t1 is the time when i is evaluating j. Closer the node is towards the destination, the less it will consume energy in communication. The updated total distance between the respondent vehicle is calculated using equation (3)

$$d_{ij_u} = \begin{cases} d_{ij} - d_j^t & \text{if } S_D \text{ is towards destination} \\ d_{ij} + d_j^t & \text{if } S_D \text{ is away from destination} \end{cases} \quad (3)$$

where S_D is the direction of the speed of respondent vehicle. The source vehicle chooses the respondent based on minimum distance and minimum computation cost of data communication towards destination and adds them to a route. The process continues until the data packets originated from the source end does not reach to the terminal end or the destination. This process of AODV does not guarantee any QoS quality as the network faces a lot of vulnerabilities. The network may face congestion in terms of data communication or security hacks as the vehicles are mobile. Mobility invites less tractability accuracy which further attracts security threats. Hence, intelligent Algorithm-based routing strategies got the attention of the researchers and the modern world computation (Wahi et al., 2021). Swarm intelligence (SI) has been observed to be one of the most adoptable approaches in VANET. SI has been a part of VANET since 2014 and SI has gained ample amount of attention by the VANET architecture. All these gives rise to number of research questions such as given below.

- How can strength of routing can be enhanced?
- How can routing be designed to consider real-time traffic conditions to improve service in VANETs?
- How can data communication can adapt to the dynamics of VANETs?
- What strategies can be employed to optimise routing for large scale VANETs?
- Which algorithms and methods can be used to optimise route discovery in VANETs to minimise energy consumption?
- How effective are SI algorithms in route selection in VANETs?
- How routing can be optimised without compromising performance?

1.2 Usage of swarm intelligence in route discovery in VANET

VANETs are becoming increasingly popular due to their ability to provide various applications, such as road safety, traffic management, and entertainment. Route discovery, which establishes the route from an origin and the desired destination within the network, is a crucial component of VANETs. SI algorithms have been extensively employed in VANETs to address challenging issues, such as route discovery. SI algorithms get their inspiration from the social behaviour of ants, bees, and other insects as well as birds. These algorithms are renowned for their decentralised, adaptive capacity to locate the best possible answer. SI algorithms may be used in VANETs to determine the best route between the origin and the endpoint while taking into account a number of factors, including network congestion, security, and QoS. In recent years, several researchers have proposed the use of SI algorithms for route discovery in VANETs. For example, (Zhang et al., 2019a) proposed a route discovery protocol in VANETs based on the ant colony optimisation algorithm. The authors showed that their protocol improved the reliability and efficiency of route discovery in VANETs. (Al-Shathry and Al-Dubai, 2019) proposed a SI-based route discovery protocol for VANETs that used the bee algorithm. The authors showed that their protocol improved the network performance and reduced the routing overhead in VANETs. (Liu and Liu, 2019) proposed an ant colony optimisation-based route discovery protocol for VANETs that considered the network security. The authors showed that their protocol improved the security and reliability of route discovery in VANETs. (Liu et al., 2019) suggested a QoS-restricted routing technique for VANETs based on the SI algorithm. The authors showed that their protocol improved the QoS and efficiency of route discovery in VANETs.

1.2.1 Grasshopper optimisation algorithm

It has been utilised in the proposed approach due to its novel approach of pairing in both exploration and exploitation phase. The usage of grasshopper optimisation algorithm (GOA) in VANETs has been extensively researched in recent years, providing promising results for improving the routing performance in these networks (Darbandi, 2017; Heidari et al., 2023). The following two papers present the usage of the GOA in the context of VANETs. (Aggarwal et al., 2021) presents a bio-inspired routing algorithm for VANETs that uses the GOA to determine the optimal route for communication between vehicles. In the second publication, (Sellami and Alaya, 2021) suggested using the GOA-based self-adaptative multi-kernel (SAMNET) network clustering algorithm for urban VANETs. The paper indicates that promising results have been obtained from research and application of the GOA in VANETs. It demonstrates its versatility in tackling research questions unique to automobile ad hoc networks by being used for both routing and network clustering applications. Its matching strategy and bio-inspired nature are emphasised as salient characteristics. In view of the observations made from the existing research inspired from SI algorithms the proposed work lists the following contributions in the presented article.

- Enhanced route discovery: By using novel decision making within grasshopper optimisation, the research brings enhancements to the route discovery process with the goal of efficiently streamlining decision-making stages.

- Rank-based mechanism implementation: SI is used in a rank-based route discovery mechanism to ensure robust and dependable route selection while reducing the negative effects of malicious nodes on route efficiency.
- Introducing GOA: The GOA is a meta-heuristic optimisation technique that provides effective solution space exploration and exploitation. It is named after the behaviour of grasshoppers.
- Application of GOA to route optimisation: GOA is used to optimise routes in vehicular Ad Hoc networks (VANETs), showcasing its ability to quickly converge to near-optimal solutions while adjusting to dynamic situations.
- Simulation and assessment: The performance of the proposed methodology is evaluated based on important QoS factors like throughput, packet delivery ratio (PDR), and delay through comprehensive simulation and assessment, demonstrating its superiority over current methods in VANET scenarios.

The remainder of the essay is structured as follows. The use of papers on route finding and optimisation using the SI algorithm is demonstrated in Section 2 as related work. The suggested work is illustrated in Section 3, and the outcomes are evaluated in Section 4. Section 4 contains the evaluated parameters based on QoS. This section also contains the comparison of the proposed work with other state of art works. The paper is concluded in Section 5.

2 Literature review

Al-Shalthry and Al-Dubai (2019) present an efficient and reliable route discovery protocol for VANETs. The authors propose a SI based approach, which makes use of ACO algorithm, to solve the issue of finding an optimal route between a source and a destination in VANETs. Through simulation studies, the suggested protocol has been assessed, and the findings demonstrate that it performs better than the current ones in terms of both the PDR and average end-to-end delay. Although, it lacks a comprehensive analysis in various network scenarios, such as densely packed nodes, inconsistent connectivity, or fluctuating traffic patterns. In a similar approach, (Aziz and Al-Otaibi, 2018) propose an efficient and secure route discovery protocol for VANETs. The authors make use of a hybrid mechanism, which combines the benefits of both ACO and trust-based model in which the ACO is fused with trust value to produce energy efficient communication. Even though, its ability to protect data confidentiality and integrity may be in doubt without a thorough examination of how resilient it is to different threats and security lapses.

Chen and Hu (2019) present a novel routing protocol for VANETs based on game theory and social network analysis. The authors propose a new routing algorithm that considers both selfishness and cooperation of vehicles in finding an optimal route. In Zhang et al. (2019a) propose a route discovery mechanism in VANETs based on SI. The authors make use of particle swarm optimisation (PSO) algorithm to find an optimal route between a source and a destination deployed in a given map. Extending the work.

Al-Shathry and Al-Dubai (2019) presented a SI based discovery algorithm for VANETs. The authors propose an SI based approach, which makes use of ACO algorithm. Unlike Aziz and Al-Otaibi, (2018) the authors completely relied on the reliable ACO algorithm. To do so, the authors prepared a gimic behaviour of ant and introduced a new fitness function to check the reliability of the node. Liu and Liu (2019) present an efficient and reliable route discovery protocol for VANETs using ACO and (Fahad and Ali, 2018) utilised the fuzzy logic-based approach to address the multiple objectives of routing such as reducing delay, avoiding congestion, and reducing transmission power consumption. The fuzzy logic approach is applied to measure the priority of each objective and to select the best routing path based on the calculated priorities. The performance of the authors' suggested method was also assessed using simulations, and it was contrasted with other protocols already in use with respect to of standard entire delay and transmission power usage. The authors claim that their approach provides a trade-off between multiple objectives and balances the trade-off by considering the priority of each objective. The authors also mention that the fuzzy logic approach makes the proposed protocol more adaptable to different network conditions. One possible drawback of the proposed protocol is that it may not perform well in complex network environments or under various constraints and objectives.

Joshua and Varadarajan (2021) presented an optimisation framework based on the firefly algorithm to address multiple objectives in routing protocols, such as minimising delay and maximising network throughput. The firefly algorithm is used to find the optimal solution by balancing multiple objectives. Using simulations, the authors assessed the performance of their suggested framework and contrasted it with other protocols already in use in terms of delay and network throughput. The findings demonstrate that the suggested framework performs better than the current protocols in terms of network efficiency and offers a decent compromise between various goals. It may be challenging to determine its superiority and generalisability across many VANET contexts without comparing against a broad range of baseline approaches. Furthermore, there is need for improvement in the multi-objective optimisation methodology to guarantee its efficacy and efficiency in real-world VANET deployments.

Aggarwal et al. (2021) proposed a bio-inspired routing protocol for VANETs based on the honeybee behaviour. The honeybee behaviour is used to determine the best routing path based on the information collected from other nodes. The reliability of the new protocol was further assessed by the authors using simulations, and it was contrasted with other protocols already in use in terms of usual total delay and network performance. The authors claim that their proposed protocol provides a better balance between multiple objectives and adapts to different network conditions by considering the behaviour of honeybees. However, the study is devoid of a thorough examination of the routing algorithm's scalability and adaptability.

Sellami and Alaya (2021) proposed a self-adaptive clustering algorithm for VANETs that adjusts its behaviour based on the network conditions. The algorithm uses multiple kernels to cluster the nodes and determine the best routing path. The performance of the suggested method was further assessed by the authors using simulations, and it was compared to other algorithms already in use in terms of overall total delay, network throughput, and network endurance. Even though it makes this claim, it is not quite obvious how flexible it is in terms of how it responds to different traffic situations, road designs, and network capacities.

Sindhwani et al. (2022) used a dynamic routing protocol to adjust to the dynamic nature of VANETs. The approach combines K-Means for cluster formation to improve the structure of vehicular networks. By facilitating effective cluster creation, the K-Means Algorithm enhances network management. Furthermore, flexibility in response to shifting network topologies and traffic conditions is guaranteed by the dynamic routing protocol. It is important to remember that, although if the study provides insightful information on the combination of dynamic routing and clustering, there may be some limits due to scalability issues in large-scale networks and the requirement for thorough testing in a variety of scenarios.

Husnain et al. (2023) presented a bio-inspired cluster optimisation model for effective routing in VANETs. To improve routing efficiency, they used a technique that optimises clustering by taking inspiration from biological processes. The paper offers an alternate viewpoint to conventional algorithms by investigating bio-inspired techniques to handle VANET difficulties. Its limitations could include the requirement for additional validation in VANET deployments in the actual world and possible considerations for the overhead brought about by bio-inspired systems. Giridhar et al. (2023) included recent studies on energy-efficient routing protocols and clustering in VANETs. They presented a heuristic optimisation-based routing protocol for VANETs in their work. The approach includes energy-efficient clustering with the goal of improving vehicle networks' overall performance. Promising results are shown by the heuristic optimisation strategy, which successfully balances the energy consumption of different vehicles. Salim et al. (2023) have concurrently presented SOMACA, a novel mobility-aware clustering technique for the network of vehicles based on swarm optimisation. The concept takes into account the dynamic nature of vehicular networks and forms effective clusters by utilising swarm optimisation techniques. It helps to enhance communication and adaptation. However, it important to remember that studies might have drawbacks, such as potential susceptibility to particular network circumstances or scalability issues in large-scale implementations. To fully evaluate these suggested techniques' robustness and generalisability in actual VANET setups, more investigation and real-world validations are required.

The literature section discusses several existing works that aims to address some specific challenges. These challenges are listed below to highlight the challenges that independent studies have aimed in their research work.

- Effective and dependable route discovery: Al-Shalthry and Al-Dubai (2019) provide a SI-based method based on the ACO algorithm to identify the best routes in VANETs with an emphasis on reducing end-to-end latency and PDR. While their protocol does not have a thorough examination for different network conditions.
- Secure root discovery: Aziz and Al-Otaibi (2018) present a hybrid mechanism for trust-based route discovery that combines an ACO model with a trust-based framework. Despite its energy-efficient communication, it lacks a complete security analysis and worries about data confidentiality and integrity.
- Selfishness and cooperation: Chen and Hu (2019) address the problem of selfishness and cooperation among vehicles in route selection with a novel routing protocol based on game theory and social network analysis.
- Optimal root discovery: The challenge of optimal route discovery was addressed by Zhang et al. (2019a) provide a route discovery technique based on PSO.
- Reliability in route discovery: To improve root discovery efficiency by addressing latency, congestion, and transmission power consumption challenges Liu and Liu (2019) and Fahad and Ali (2018) use ACO and fuzzy logic-based techniques, respectively.
- Optimisation framework for multiple objectives: Joshua and Varadarajan (2021) provided firefly-based optimisation framework to address challenge of network throughput and reduce latency. This framework provides a reasonable trade-off between several objectives.
- Dynamic network condition: Aggarwal et al. (2021) presented a bioinspired routing protocol that was inspired by the behaviour of honeybees to balance various goals and adjust to varying network conditions.
- Dynamic traffic challenge: Sellami and Alaya (2021) presented a self-adaptive clustering algorithm for VANETs that modifies behaviour in response to address challenges of network and conditions and traffic scenarios.
- Dynamic routing challenge: Sindhwani et al. (2022) improved network administration and adjust to the dynamic nature of VANETs by combining a dynamic

routing protocol with K-Means clustering, albeit scalability problems in large-scale networks may occur.

- Routing efficiency: Husnain et al. (2023) provide an alternative to traditional methods by putting forth a bio-inspired cluster optimisation model to improve routing efficiency in VANETs.
- Dynamic clustering: To enhance overall network performance, Giridhar et al. (2023) introduces a heuristic optimisation-based routing protocol that focuses on energy-efficient clustering. To improve communication and adaptability in vehicle networks, Salim et al. (2023) provide SOMACA, a mobility-aware clustering technique based on swarm optimisation.

Notwithstanding their progress, these methods can have drawbacks like vulnerability to particular network circumstances or scalability problems, necessitating additional research and validation in actual VANET implementations. Thus, the related work section shows that many researchers have worked on similar ideas to overcome the challenges of VANETs. However, the present paper brings multiple novel elements that set it apart from earlier research in the field as follows:

- Innovative methods for generating decisions: This study is notable for developing and utilising methods for generating decisions inside the grasshopper algorithm. These methods are designed to improve the discovery and extraction stages, which leads to more efficient routing strategies. This creativity distinguishes the current investigation from other research that might not have looked into or included such unique approaches to decision-making.
- Advanced fitness function implementation: To enhance the GOA's performance, the work integrates a fitness function. This sophisticated fitness feature is made to maximise route finding while using the least amount of energy possible. Compared to earlier studies that might have relied on traditional fitness functions or algorithms without such improvements, the integration of this innovative function marks a change.
- Assessment and contrast with cutting-edge algorithms: By putting the suggested algorithm through a thorough review, the study goes beyond simple algorithm development. It highlights QoS features by contrasting the recommended algorithm with other cutting-edge algorithms. This comparative analysis sets the current work apart from previous research that might have concentrated just on algorithm creation without conducting a full review by illuminating the algorithm's relative strengths and limitations.
- Examining efficiency metrics: The study presents a novel method for assessing the computing cost in terms of delay and packets transferred that, in turn, reflect the efficiency of the routing process. The study stands out from other works that might not have given such considerations in their judgement for communication.

In summary, the combination of novel decision-making strategies, the application of a sophisticated fitness function, a careful analysis, comparison with the most recent algorithms, and an emphasis on efficiency indicators are what make the current study novel. Together, these characteristics set it apart from earlier research and further the field's understanding of VANETs.

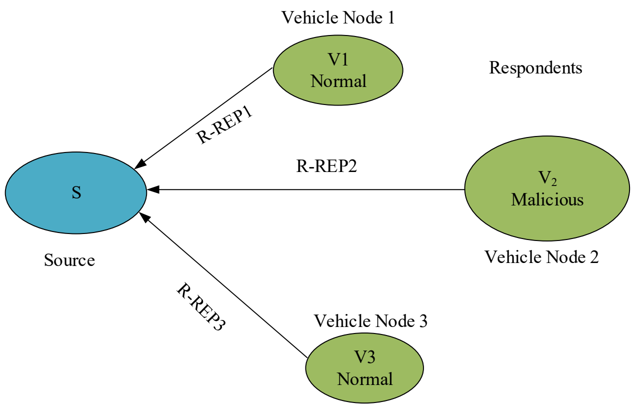
3 Proposed work

The proposed work aims to improve the route discovery process by involving grasshopper optimisation at the decision-making stage. The below sections first describe the route discovery process that forms the 1st phase of the proposed work. This is followed by the description of the implementation architecture of the grasshopper, including improvisation at the exploitation stage of the optimisation algorithm. The second phase presents the optimised route discovery process describing the overall work flow. The detailed processes in both phases are described below.

3.1 The route discovery phase

The source end broadcasts a RREQ to adjacent vehicles in order to learn the path from the origin end to the target end because RSU-based information is only capable of providing basic information (Liu et al., 2019). In case of V2V, the source vehicle will have to broadcast to the nearby vehicles for specific information. For, illustration refer Figure 1. When the source node broadcasts the requirement as RREQ, the nearby vehicles responses to the broadcast as RREP.

Figure 1 A route response with malicious node in the list (see online version for colours)



The source node will have to choose a node in order to communicate. Here the trust of the vehicle plays a vital role. The respondent might be malicious in terms of tampering the information that would further increase the overall route time of the considered vehicle. To prevent the system from losses, the proposed work utilises a rank-based route discovery mechanism that utilises SI. SI has been observed to be utilised frequently in research articles for a long time due to its abilities in the selection approach (Brezočnik et al., 2018). Joshua and Varadarajan (2021) used SI based throughput and PDR based fitness function in the algorithm for the selection of the most appropriate node from the respondent list based on throughput and latency parameter. Aggarwal et al. (2021) work has been observed to be carried out with change in group behaviour of the artificial bees to reject the request before the final analysis. SI algorithm architecture is based on NP hard problems that are used to solve meta-heuristic oriented approaches (Sellami and Alaya, 2021). The proposed work uses GOA based on a new Levy distribution mechanism for route discovery and hence is named as GOA-r with improvisation in the exploitation phase.

3.2 Grasshopper optimisation algorithm

The GOA is a type of meta-heuristic optimisation algorithm that draws inspiration from the social behaviour of grasshoppers. It is a population-based algorithm that operates on a population of candidate solutions and iteratively updates their positions and velocities to converge to the optimal solution (Meraihi et al., 2021). GOA is based on three key behaviours of grasshoppers: cohesion, assignment, and separation. The algorithm tries to mimic these behaviours to optimise a given objective function. The Cohesion behaviour ensures that the individuals move towards the centre of mass of the population. The equation for cohesion can be represented as follows:

$$C = (1/n) * \sum (Xj - Q) \tag{4}$$

C is the population's cohesiveness vector, n is the size of the population, Xj is the position of the j^{th} individual and Q is the position of the current individual.

The Assignment behaviour ensures that the individuals move towards the target. The equation for assignment can be represented as follows:

$$A = \left(\frac{t}{s}\right) * (P - Q) \tag{5}$$

where A is the assignment vector, t is the time parameter, s is the distance between the current individual and the target, Y is the position of the target and Q is the position of the current individual. The Separation behaviour ensures that the individuals move away from each other to avoid collision. The equation for separation can be represented as follows:

$$S = (1/n) * \sum (Xj - Q) / \|(Xj - Q)\| \tag{6}$$

where S is the separation vector, n is the number of individuals in the population, Xj is the position of the j^{th} individual, X is the position of the current individual and (Xj–Q) is the Euclidean distance between the two individuals.

The velocity of each individual is updated based on the cohesion, assignment, and separation behaviours as follows:

$$V = w * V + C + A + S \tag{7}$$

where V is the velocity of the current individual, w is the weight parameter and C, A, and S are the cohesion, assignment, and separation vectors respectively. The position of everyone is updated based on its velocity as follows:

$$Q = Q + Z \tag{8}$$

where Q is the position of the current individual and Z is its velocity.

GOA also uses an exploration and exploitation behaviour to balance the exploration of the search space and the exploitation of the promising regions. The weight parameter w determines the exploration and exploitation behaviour of the algorithm. A low value of w means more exploration and a high value of w means more exploitation.

The steps of the GOA are as follows:

1 Randomise the number of potential answers.

2 Determine the value of each population member's goal function.

3 Update the velocity and position of each individual based on the Cohesion, Assignment, and Separation behaviours and the exploration and exploitation behaviour.

4 Repeat steps 2 and 3 until a stopping criterion is met.

5 Return the best individual in the population as the optimal solution.

It is important to understand that the total cost of the optimisation algorithm could be determined by designing a fitness function that takes energy efficiency, execution time, and idle time into account (Mafarja et al., 2018; Qin et al., 2021). To accomplish the intended trade-offs between conflicting objectives in the optimisation process or to incorporate these factors, the weights assigned to each of the following factor would be precisely calibrated.

- Idle time: One important component is idle time, which is the amount of time the server spends compiling the previous queued task while the current process is on hold. For instance, the server has five requests piled up before the C1 request, and if each request reply need a time of 2 secs. Then, the idle time for this case will be of 10secs
- Execution time: The amount of time needed to finish a specific job or communication is called the execution time. By giving preference to solutions that enable tasks to be completed more quickly, the fitness function may aim to maximise execution time. The execution time, which includes both the idle and task-completion times, is computed by the fitness function. This guarantees that the amount of time required to complete the assignment is accurately reflected. For similar example as stated earlier, the execution time will be idle time and the time required to reply C1 request

which will be 10 sec + 2 sec = 12 sec, (assuming the reply to C1 also consumes 2 sec)

- Energy factors: Energy efficiency is an important factor to take into account, particularly in vehicular networks where there are limited resources for the vehicles. The fitness function incorporates the energy efficiency component. It takes into consideration the energy used for both execution and idle time

In recent years, the GOA has been successfully applied to various optimisation problems and has been shown to be a promising optimisation method even for VANETs due to following features and advantages over the traditional routing approaches in VANETs:

- Flexibility in changing circumstances: This swarm-based algorithm is more responsive than static routing techniques because they can adjust to the constantly shifting traffic patterns and network topologies in VANETs.

Figure 2 The overall work flows (see online version for colours)

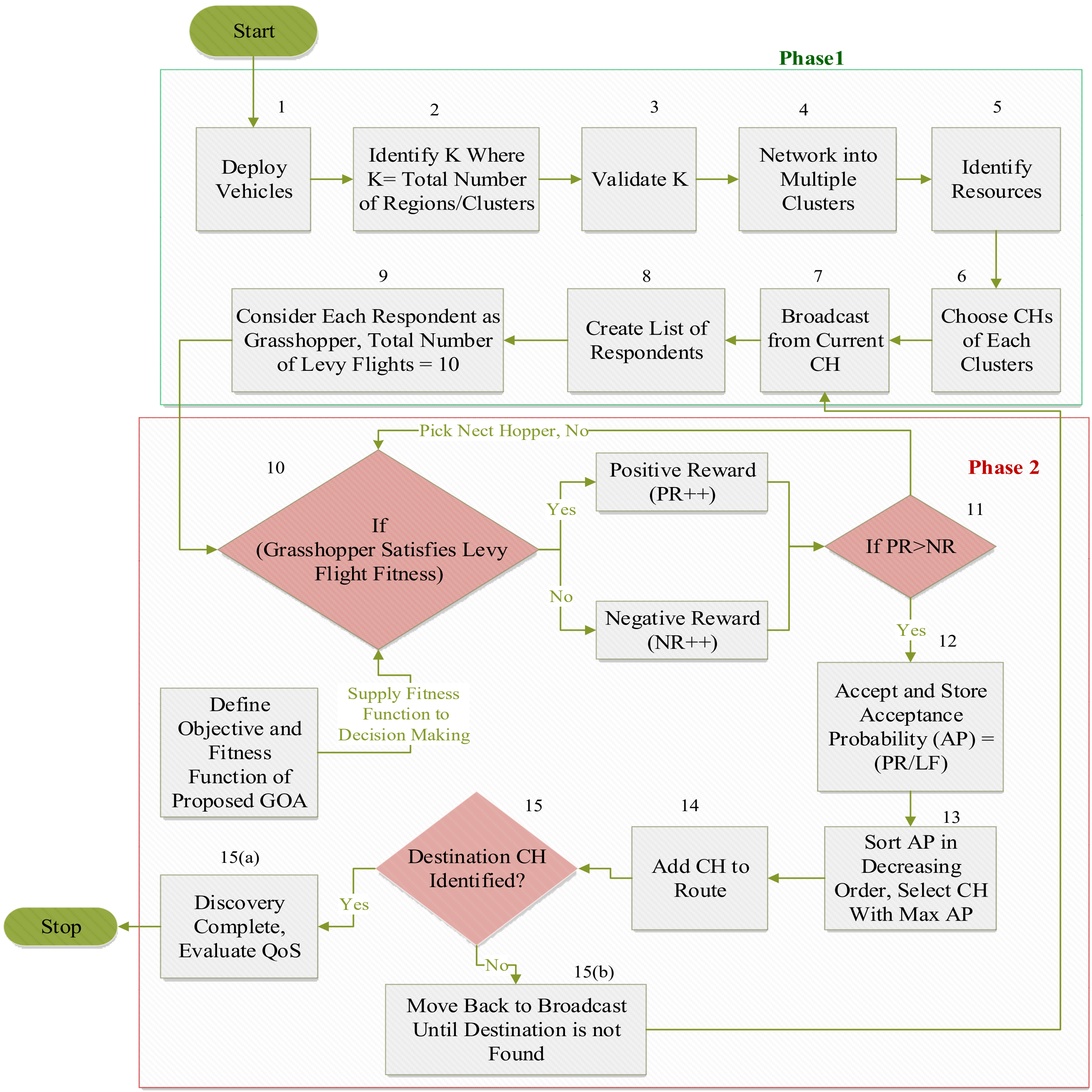


Figure 3 Vehicle deployment

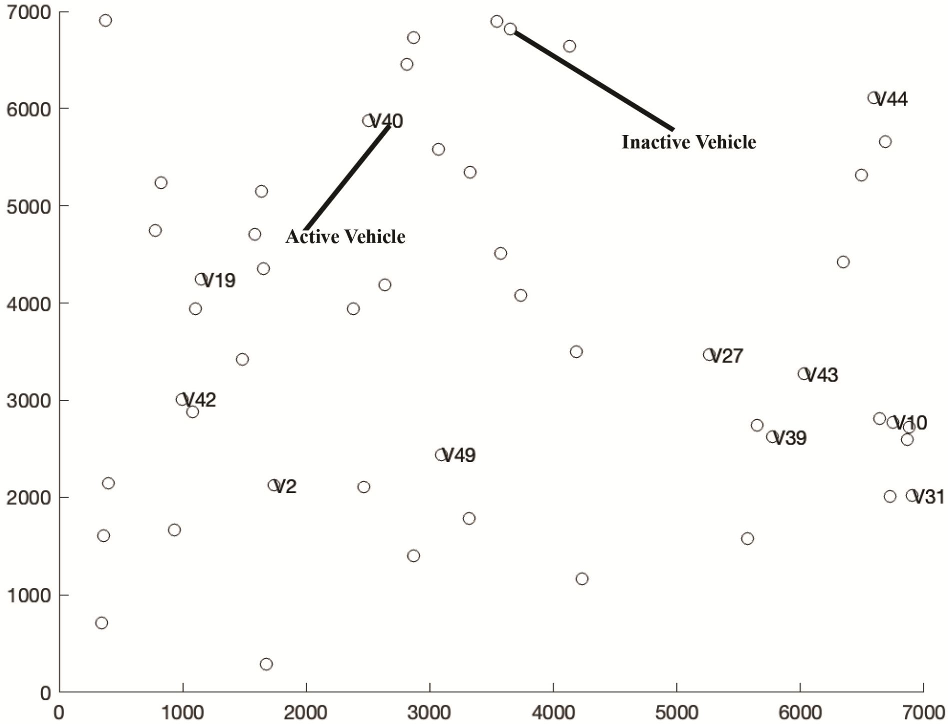
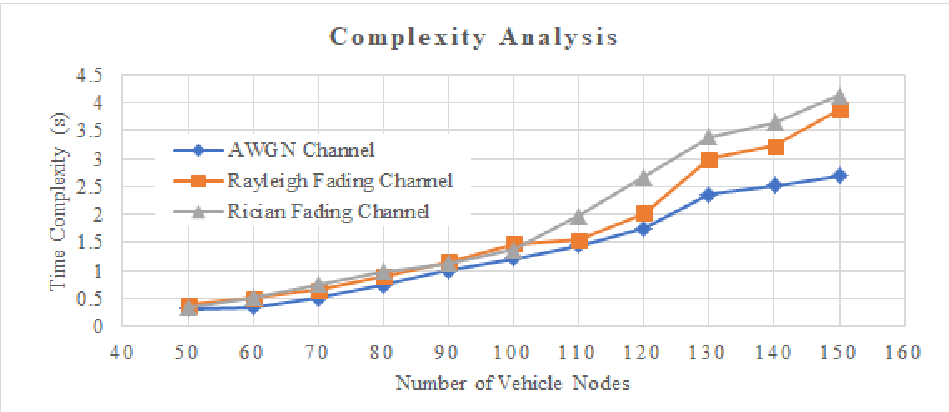


Figure 4 Channel complexity analysis (see online version for colours)



- Independent decision-making: Autonomous decision-making by cars is made possible which function in a decentralised fashion by utilising local information. This can improve VANETs' resilience and scalability.
- Effective solution space exploration: These are excellent at effectively exploring a large solution space. This feature is useful in VANETs, where it's critical to identify the best routes under dynamic situations.
- Enhancing communication resources: Vehicles can improve their communication patterns with the aid of optimisation algorithm, which lowers traffic and boosts data transmission efficiency in VANETs overall.
- Accelerated convergence to ideal solutions: It frequently converge fast to close to optimal solutions, which is useful in dynamic situations requiring swift route optimisation.
- Scalability: Because the algorithm divides up the decision-making process among multiple organisms, they are by nature scalable. Scalability like this is advantageous for large-scale VANETs with many of cars.

However, like any other meta-heuristic algorithm, it may get stuck in local optima and may not always converge to the global optimal solution.

3.3 Route optimisation phase

As it has been illustrated and defined in the introduction section of the draft that the proposed work uses SI based

GOA algorithm for the optimisation of the route, the work flow of the proposed work can be explained using Figure 2.

The proposed work is divided into 16 steps grouped into two phases where each conditional statement has two subsets.

- Phase 1 describes the clustering process with cluster validations mechanism.
- Phase 2 represents the route optimisation process.

The entire work simulation has been performed in MATLAB due to its easy programming and simulation architecture. A random road map has been designed with 'n' number of vehicles in the simulation.

The vehicles are deployed with random location on the map as represented in Figure 3. The proposed work considers the following assumptions.

a The vehicles can communicate with each other

b The vehicles are using additive white gaussian noise (AWGN) channel for lower computation complexity. This is due to the fact that simulation performed using AWGN channel exhibited least complexity in comparison to Rayleigh and Rician Fading Channels with increase in the number of vehicles in the network as illustrated in Figure 4. In other words, it reflects minimal computation complexity of the proposed work using AWGN channel.

c The vehicles can both receive and transfer request to each other.

The steps for vehicle deployment are illustrated as follows.

1 Deploy n number of vehicles in the network with 'w' width and 'h' height.

2 Using k- means, divide the nodes into 'k' number of clusters according to their original positions in space. The nodes or automobiles are travelling between 40 and 60 km per hour.

3 In order to validate the most suitable count for the cluster, the clustered data is passed to k-nearest neighbour (k-NN) classifier. The network division is done in such a manner that $5 \le k \le 8$.

Figure 5 Cluster assignment for k = 5 (see online version for colours)

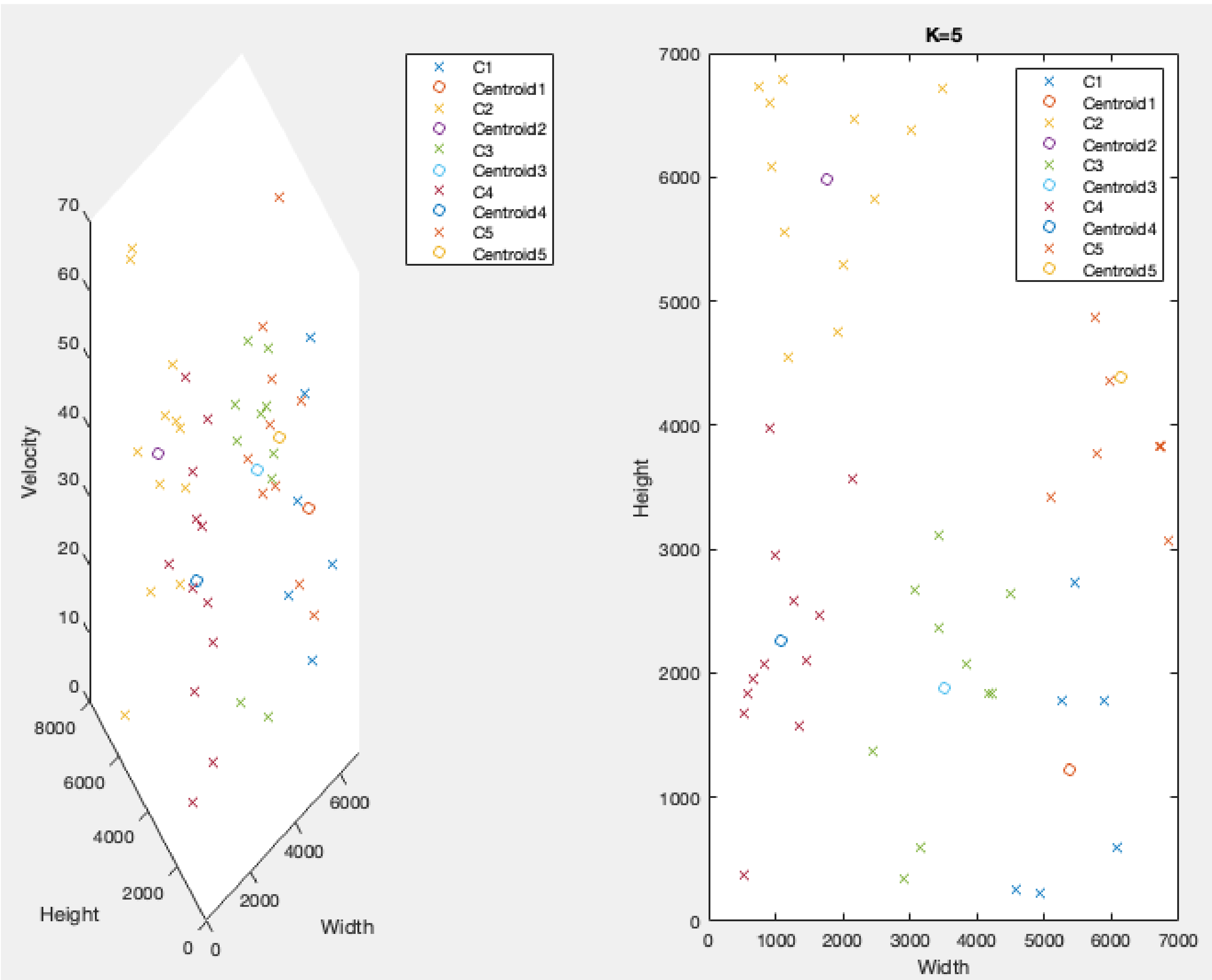
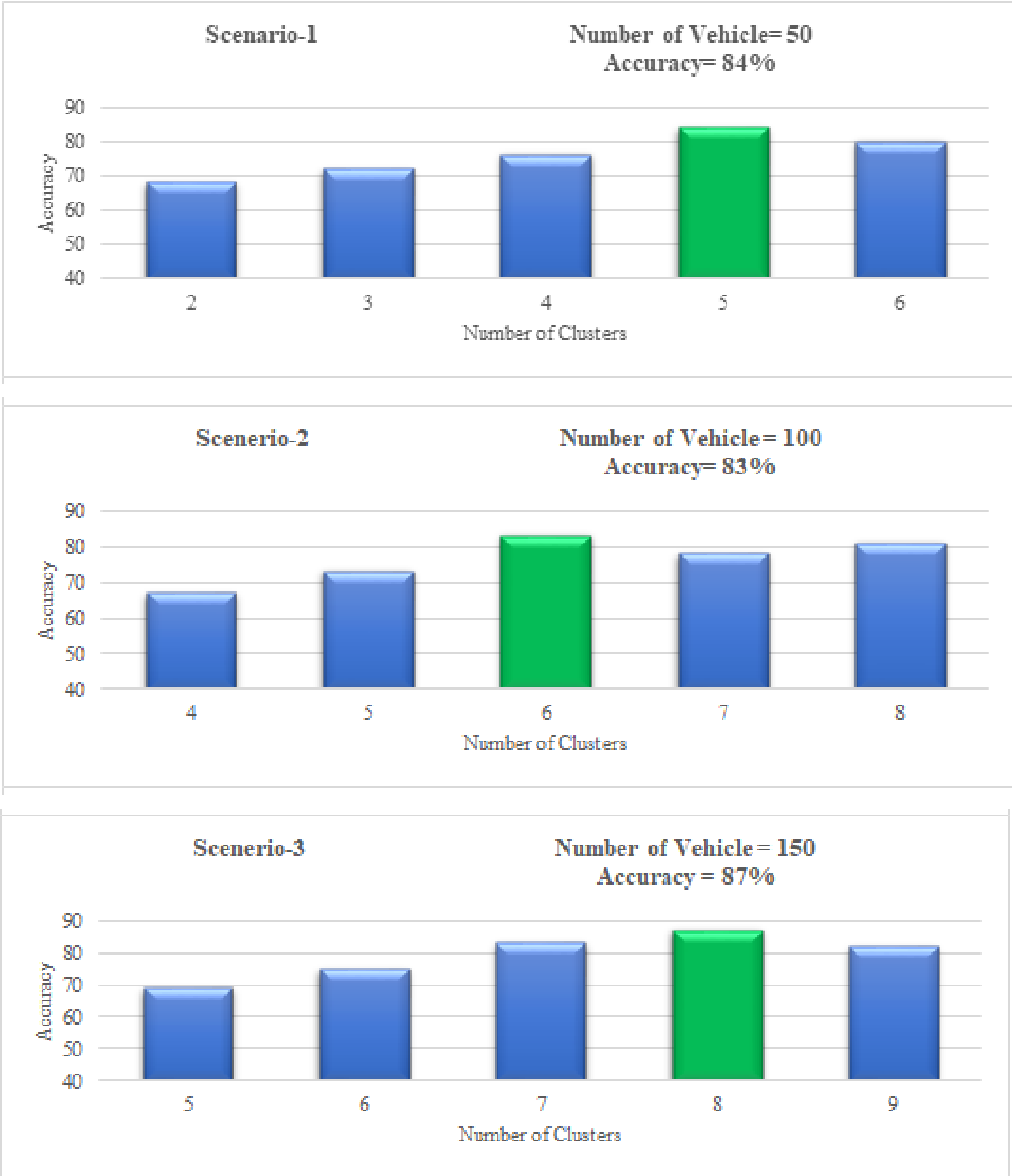


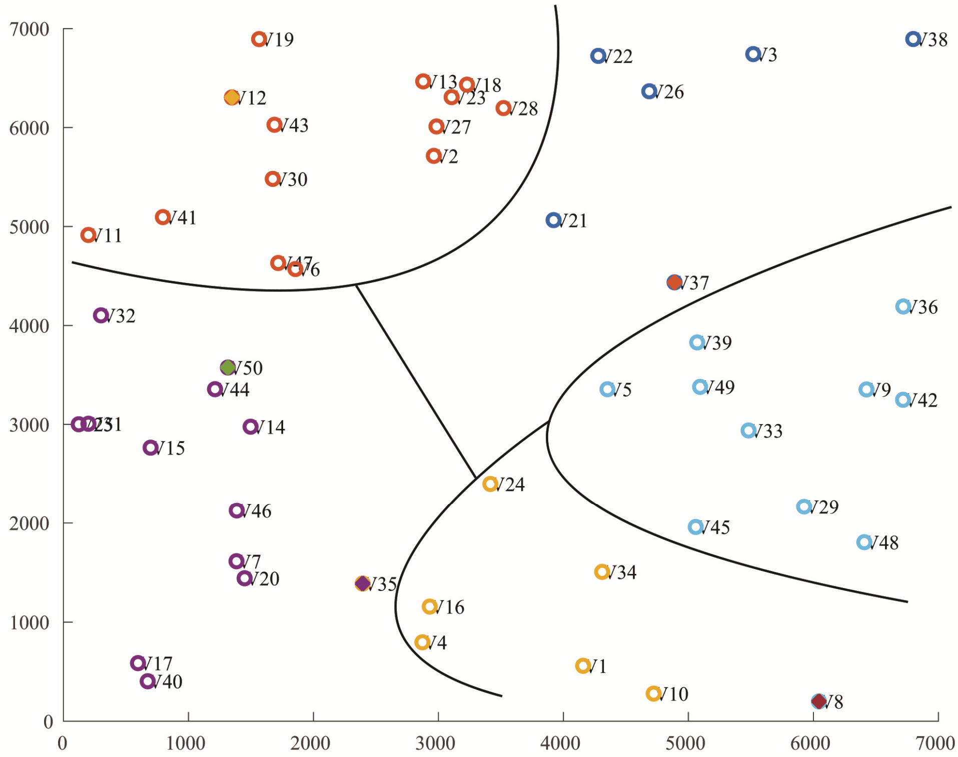
Figure 6 K-classification accuracy (see online version for colours)



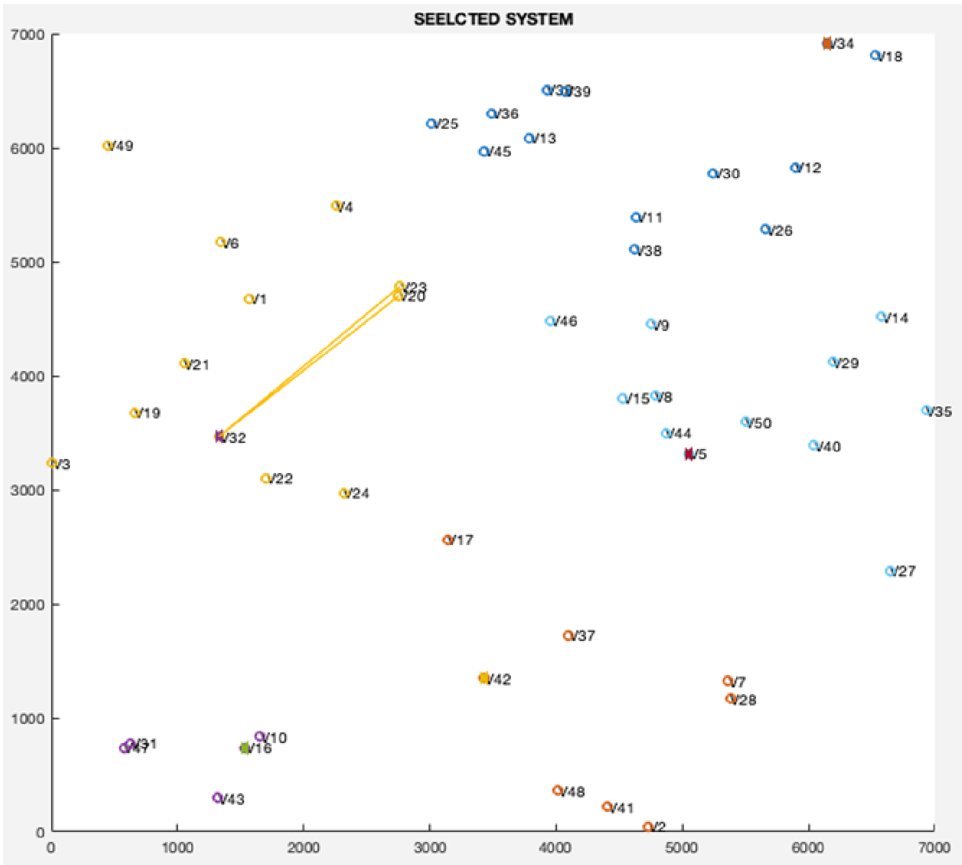
(b)

The clustering has been done on the base of node location and vehicle known speed and a 3D speculation is created. The clustered data is passed with cluster number as ground truth and $\{x_i, y_i, v_i\}$ as input set to Naïve Bayes. With the maximum accuracy in the cluster assignment, the network is distributed with k number of clusters. For various scenarios, the proposed work has been identified to be on various number of k values. The proposed selection criteria has resulted into increase in k-values with a significant increase in total number of vehicles in the list in the given area of deployment in the network. Figure 6 represents the k-selection policy in which three scenarios are discussed and evaluated based on classification accuracy. It is observed that when the number of vehicles is restricted to 50, the highest and best accuracy is obtained with 5 clusters. However, as the number of vehicles is increased to 100 and 150, highest accuracy is obtained with 6 and 8 clusters, respectively.

Figure 7 (a) Implemented scenario 7 (b) Implemented scenario (see online version for colours)



(a)

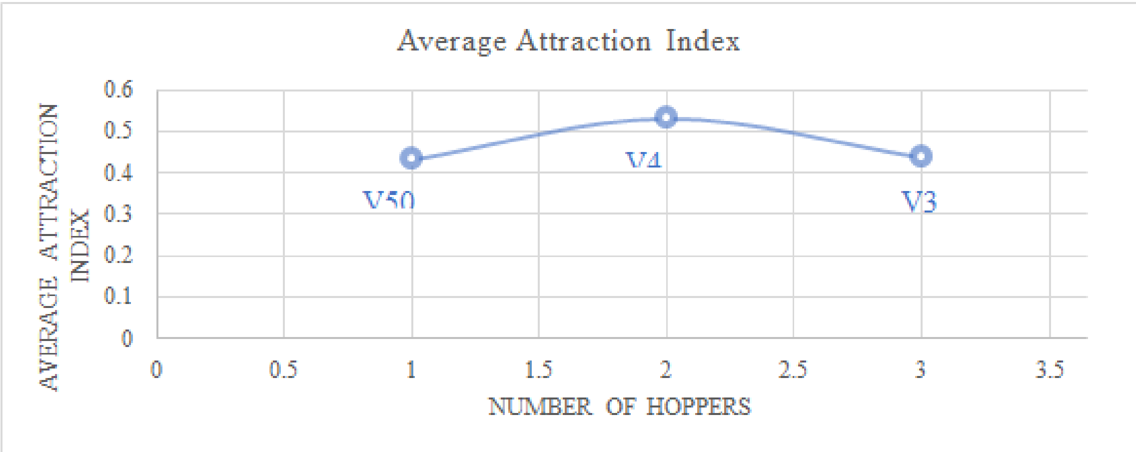


(b)

Table 1 Levy flight results

Levy flight	*V50*	*V40*	*V3*
Lf 1	0.20038076	1	0
Lf 2	0.38421631	0.89274576	0.07364054
Lf 3	0.1819972	0.7962171	0.15464513
Lf 4	0	0.70934144	0.24375018
Lf 5	0.16379748	0.61377833	0.34176574
Lf 6	0.34397471	0.50865909	0.44958286
Lf 7	0.54216966	0.39302812	0.56818168
Lf 8	0.76018411	0.26583429	0.69864039
Lf 9	1	0.12592137	0.84214496
Lf 10	0.73620252	0	1

Figure 8 The average AI calculation (see online version for colours)



As shown in Figure 6, the value of k classification accuracy increases with the increase in total deployed vehicles that depicts the significance of increasing total number of vehicles per capita area. In order to do that, as discussed earlier in this section, the proposed work uses Naïve Bayes classifier and the ordinal measures are as follows.

$$X_i = C_w \sum_{j=1}^{lf} (p-q) \times S + T_d \tag{9}$$

where C_w is the weight of the intertia, lf is total number of Levy flights which in case of proposed work is 10. In case of proposed work, C_w is the group value of the parameters considered viz. the distance of the CH from its base station and total idle time ($Idle_t$) that can be evaluated using equation (9)

$$S = \frac{br_j}{\left|d_{jb} + l_j\right|_{norm}} \tag{10}$$

where d_{jb} is the distance from the respondent CH to the base station and l_j is the latency for CH_j. The l_j can be calculated using equation (11).

ObjG ≅ ∀$CH_j\{j = 1 \ldots k\}$Argmin(l) where l is the idle latency in the network. The latency can be calculated as follow

$$l = \forall_j \left(\frac{T_p}{b_r}\right) \tag{11}$$

where T_p is the total number of data packets in the buffer to be executed and b_r is the execution rate of responding CH_j. The seeker selects the CH with best attraction value in all Levy.

The proposed GOA is inspired by the algorithm architecture in GOA algorithm. The proposed GOA algorithm is presented in the following steps illustrated in proposed GOA algorithm.

Proposed grass hopper algorith

```
For i in CHs
  For j in GOAall
    if i ≠ j
      For k = 1: lf
        Aij = Calculate Allignment(i, j).equation (9)
        Cij = Calculate Cohesion(I, j) equation (10)
        f = fitGOA(Aij, Cij)
        If f==1
            R++
        Else
```

```
                R- -
            End if
        End Fork
        If R++ > 0
            Sp[j] = R++ % selection probability
        Else
            Sp[j] = 0
        End if
    End Forj
    Choose CH with max Sp
End Fori
```

It has been mentioned that the present research work mainly focuses on creation and use of novel and innovative decision making within the grasshopper algorithm. In the modified GOA, the classic random pairing technique is swapped out with a strategic method. The main idea here is to minimise the latency and total idle time of the communication. Hopper pairing behaviour has been more standardised as a result of the adoption of a preset selection policy in place of the previous random pairing method. In order to achieve the main goals of the algorithm, this function is especially designed to decrease idle time as well as latency. The pairing procedure includes 30% of the grasshopper population and attraction index that spans over 10 Levy fights is provided in Table 1 for illustration purpose for 3 CHs. Instead of the randomness included in the original grasshoppers algorithm, this intentional alteration to the pairing and assessment behaviours improves the system's functionality by offering a more purposeful and targeted approach. The proposed grasshopper can be illustrated using the following work example that is extracted from the designed simulation model.

As shown in Figure 7, 50 vehicles have been deployed in an area of 7 km^2 in terms of a 2d network diagram. Consider V44 is the source for now and the CH for V44 is V45 marked with blue dot in the same region. The regiofigns are separated by thin lines and the vehicles are marked with different colours to show the separation in a clean manner. Here the source will deliver the data to its concerned CH and total number of elements in the best proposed route is 2 as R= {44, 45} as shown in Figure 6. Now the CH has three nearby options viz. V40 at the left most bottom, V50 at the left most top and V3 at the diagonal. The attraction index in 10 Levy flights for all these 3 CHs are listed in Table 1 as follows.

The average attraction index for all the three CHs can be easily predicted using Figure 8 as follows.

Hence, V40 is added to route and the current R value is as R= {44, 45, 40}. The process repeats itself until the designation is not attained.

Based on the selection mechanism designed as the proposed selection technique, the proposed work is evaluated for throughput, average latency, and PDR and is illustrated in the next segment.

4 Result and simulation analysis

The proposed approach is assessed based on several QoS parameters including throughput, PDR, and delay. The results are comparing the performance of a proposed approach to two existing approaches, Fahad and Ali (2018) and Joshua and Varadarajan (2021) in a VANET scenario with 150 vehicles. The computation formula used for the calculations of each QoS parameter is discussed as follows:

1 Throughput: It is the amount of data transmitted per second (in packets per second – p/s)

$$Throughput = {Packets_{received}}/{Time} \tag{12}$$

b PDR: It is the proportion of packages that arrive at their destination as intended.

$$PDR = {Packets_{received}}/{Packets_{transfered}} \tag{13}$$

c Delay: It is the amount of time (in seconds) needed for a packet to be transferred from its originator to the recipient.

$$Delay = Time_{packetreceived} - Time_{packettransfered} \tag{14}$$

4.1 Comparative analysis

In order to justify the effectiveness of the proposed work, a comparative analysis is performed against two studies for all the three QoS parameters used in the study. The throughput analysis for three studies including proposed and the existing ones is given in Table 2. This is followed by Table 3 and Table 4 that provides parametric values of the PDR and delay analysis, respectively. The number of vehicles used in this comparative analysis ranges from 50 to 150 to reflect the practical aspects of the study.

Table 2 Throughput analysis

Number of vehicles	*Throughput proposed p/s*	*Throughput (Fahad and Ali, 2018)*	*Throughput (Joshua and Varadarajan, 2021) p/s'*
50	8461.3594	7715.3485	6968.9026
60	8386.1822	7469.0746	6964.7779
70	9141.5262	8538.8939	8220.3639
80	8603.8281	8202.6862	7479.4161
90	8593.9486	7798.6818	8355.9622
100	8445.0071	7293.3843	8292.8618
110	8418.9976	7755.4926	6789.9233
120	8745.546	8408.5525	7876.7558
130	8855.3059	8260.0205	8199.7258
140	8745.5336	8441.2523	8160.9584
150	9178.7332	9150.0275	7873.0868

Based on the throughput values listed in Table 2, using the grasshopper algorithm in the proposed work, an average throughput of 8741.718324 packets per second is observed.

In comparison to existing research works, the throughput average throughput by Joshua and Varadarajan (2021) is even lower at 7899.2939 p/s, while that of Fahad and Ali (2018) is at 8194.293358 p/s. This implies that the proposed work performs better than the strategies described in Joshua and Varadarajan (2021) as well as Fahad and Ali (2018). The grasshopper algorithm's increased average throughput suggests that it is useful in raising data transmission rates, which may enhance network performance in VANETs.

Table 3 PDR analysis

Number of vehicles	*PDR proposed*	*PDR (Fahad and Ali, 2018)*	*PDR (Joshua and Varadarajan, 2021)*
50	0.8858187	0.8089928	0.7564025
60	0.9397381	0.9246531	0.8257535
70	0.8979059	0.7902922	0.8837813
80	0.902703	0.8723506	0.8790965
90	0.8969098	0.791303	0.7664685
100	0.9745791	0.9683263	0.8787969
110	0.9037184	0.8430826	0.7695326
120	0.9569282	0.8825721	0.9243169
130	0.9832205	0.8606647	0.8726773
140	0.9191933	0.8205293	0.8589361
150	0.9288828	0.800903	0.8533005

Table 4 Delay analysis

Number of vehicles	*Delay proposed sec*	*Delay (Fahad and Ali, 2018)*	*Delay (Joshua and Varadarajan, 2021)*
50	3.5745416	4.0038835	3.6021099
60	3.5908352	4.1464687	4.0415014
70	4.5768284	5.0840804	4.5891828
80	5.1398593	6.4025882	5.6295264
90	4.7750469	5.4429143	4.8740253
100	5.3323278	5.9859073	5.9782675
110	6.1638012	7.1016203	6.6315153
120	7.2786166	8.2294319	7.5527651
130	7.6054157	9.3938064	8.3161109
140	8.2006802	9.5694322	9.6972542
150	8.3725906	9.5491003	9.8061538

Table 3 presented the PDR analysis of the three studies for 150 vehicles in the network. The proposed work demonstrated an average PDR of 0.928576546. In comparison to this, Joshua and Varadarajan (2021) reported a marginally higher PDR of 0.85295486, whilst Fahad and Ali (2018) recorded a PDR of 0.848126652. It is observed that the grasshopper algorithm's considerably higher average PDR suggests that it can enhance packet delivery dependability in VANETs, which is essential for maintaining efficient vehicle communication.

Table 4 presents the delay analysis with an average delay of 6.331885212 seconds for the proposed work Joshua and Varadarajan (2021) reported a marginally lower delay of 6.950374768 seconds, while Fahad and Ali (2018) reported a larger delay of 7.356881144 seconds. The efficacy of the suggested grasshopper algorithm in reducing communication latency is demonstrated by its lower delay when compared to Fahad and Ali (2018)and its equivalent performance when compared to Joshua and Varadarajan (2021). Thus, enhancing VANETs' general performance and responsiveness.

In comparison to previous research, the suggested optimisation strategy utilising the grasshopper algorithm appears to produce gains in throughput, PDR, and latency based on the average values that have been presented. These results highlight the potential of nature-inspired algorithms to improve the efficiency and dependability of vehicular communication systems by improving the performance of routing protocols in VANETs. The suggested approach's scalability and resilience in a variety of VANET circumstances can be confirmed by additional research and testing.

To calculate the average improvement % of proposed with Fahad and Joshua for each parameter, we use the following mathematical formula:

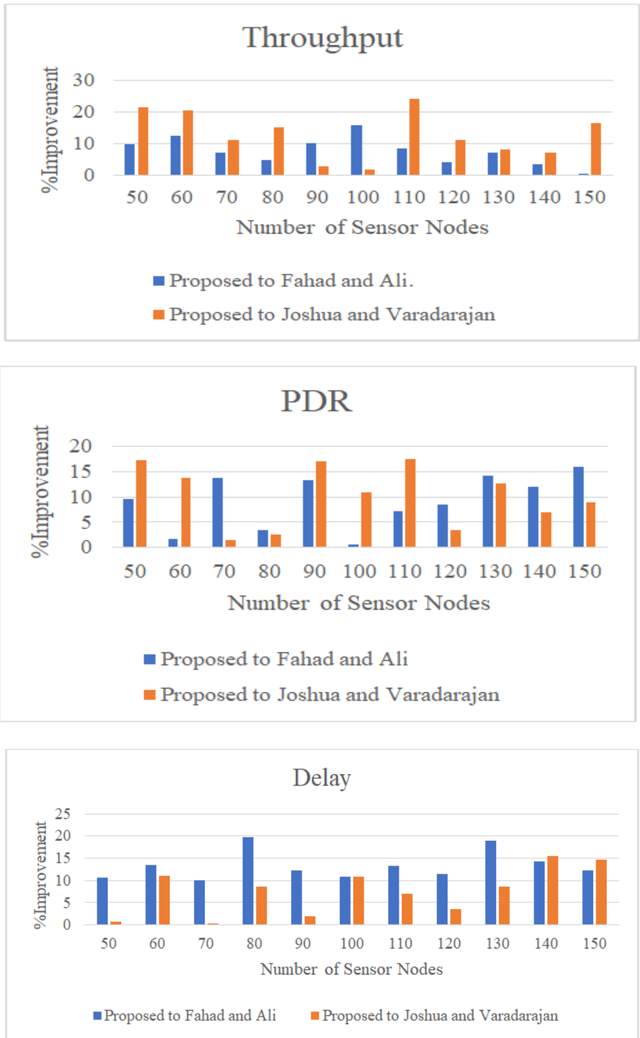
$$\%Improvement = \left[\frac{(Proposed - Existing)}{Existing}\right] x\ 100\% \quad (15)$$

- Average improvement % for throughput:
  - a With Fahad and Ali (2018): [(8741.718324–8194.293358)/8194.293358] × 100% = 6.68%
  - b With Joshua and Varadarajan (2021): [(8741.718324–7899.2939)/7899.2939] × 100% = 10.68%
- Average improvement % for PDR:
  - a With Fahad and Ali (2018): [(0.928576546 - 0.848126652)/0.848126652] × 100% = 9.47%
  - b With Joshua and Varadarajan (2021): [(0.928576546–0.85295486) / 0.85295486] × 100% = 8.84%
- Average improvement % for delay:
  - a With Fahad and Ali (2018): [(7.356881144–6.331885212)/6.331885212] × 100% = 16.15%
  - b With Joshua and Varadaraj (2021): [(7.356881144–6.950374768)/6.950374768] × 100% = 5.86%

Figure 9 provides a graphical interpretation of the %improvement observed by the proposed work over the two existing studies for each variation in the number of sensor nodes in the network. The proposed method shows an average throughput improvement of 10.68% and 6.68%, over the two studies Fahad and Al (2018) and Joshua and Varadarajan (2021), respectively. Similarly, the PDR of the proposed approach is also improved by 9.47% and 8.84% in comparison to Fahad and Ali (2018) and Joshua and

Varadarajan, (2021), respectively. Moreover, the delay of the proposed approach is reduced by an average of 16.15% and 5.86% compared to Fahad and Ali (2018) and Joshua and Varadarajan (2021), respectively. Thus, the proposed work exemplified noticeable gains in network performance. These findings highlight how well the suggested routing optimisation technique works to improve the efficacy, dependability, and responsiveness of communication in VANETs, which advances the field of vehicular networking technology.

Figure 9 Percentage improvement for each scenario (see online version for colours)



In view of the distinguishing performance of the proposed work, it has significant theoretical as well as industrial contributions. In exploring potential theoretical extensions or variations of the proposed grasshopper algorithm, the goal is to enhance its effectiveness and adaptability in route discovery tasks. One potential avenue for improvement involves incorporating dynamic adaptation mechanisms inspired by adaptive systems or machine learning principles. By enabling the algorithm to adjust its strategy dynamically based on feedback from route discovery iterations, we can enhance its ability to navigate changing environments and optimise route selection. Additionally, integrating multi-objective optimisation techniques could enable the algorithm to balance conflicting objectives, such as minimising travel time while maximising resource utilisation, thus providing a wider range of personalised route options. These enhancements build upon the foundational principles of the original algorithm by introducing adaptive learning and broader optimisation capabilities, ultimately leading to more robust and tailored solutions for route discovery challenges.

Logistics optimisation helps logistics firms plan their routes more effectively, which reduces costs and enhances supply chain management.

Similarly, from the commercial point of view it has the following significant industrial contributions:

- It improves urban traffic flow, lessens congestion, and boosts the effectiveness of the transportation infrastructure.
- It improves users' overall navigation experiences by offering more precise and effective personalised route options.
- By streamlining routes for ride-sharing and delivery drivers, this approach boosts productivity and client happiness.
- It enhances disaster management efforts by enabling faster response times and resource allocation in emergency scenarios.

5 Conclusions

The incorporation of intelligent platforms has greatly improved the information technology-based vehicle traffic monitoring and control. VANETs are being used in modern applications to demonstrate enhanced capabilities in managing various traffic-related applications, encouraging driver safety, and successfully addressing obstacles like traffic jams and detours. The GOA was used in this work as a SI technique to find the optimal paths between source and destination locations while retaining service quality. Route discovery is crucial to the optimisation of these applications.

The article presents novel decision-making behaviour through the use of an improved fitness function for the grasshopper algorithm that enables the best route discovery while using the least amount of energy. The exploitation phase of the GOA saw notable advancements that improved its efficiency in routing procedures. In order to evaluate computing costs and ensure an assessment of energy efficiency, the research makes use of execution time and idle time measures. The thorough analysis highlights the algorithm's efficacy in various scenarios by altering the deployment area and vehicle count. The contributions of the study include the development of new methods for generating decisions, the application of a sophisticated fitness function, and a detailed assessment and comparison with the latest algorithms, with a focus on QoS attributes. The work is evaluated using different scenarios by varying the number of vehicles from 100 to 150 and the deployment area from 3,000 m^2 to 5,000 m^2. The performance analysis in terms of throughput, PDR and delay shows that the work exhibited ≈5% to ≈16% over the existing approaches used in the comparative analysis. In future, authors will extent the present work by including a detailed analysis including number of scenarios to present a real-time application for traffic management.

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