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Localizing non-line-of-sight nodes in Vehicluar Adhoc Networks using gray wolf methodology

Ramu Kaviarasan | **Pillutla Harikrishna**

Department of Computer Science and Engineering, Rajeev Gandhi Memorial College of Engineering and Technology, Nandyal, Andhra Pradesh, India

Correspondence
R. Kaviarasan, Assistant Professor, Department of Computer Science and Engineering, Rajeev Gandhi Memorial College of Engineering and Technology, Nandyal, Andhra Pradesh, India.
Email: kaviarasanr64@pec.edu

Summary

Vehicular ad hoc networks (VANETs) evolved by adopting the principles of mobile ad hoc networks. This network has been designed to deploy safety related application in vehicular node in the less chaotic environment in road scenarios. Vehicles exchange emergency messages through direct communication. In a practical situation, a direct communication between the vehicles is not possible, and it is prohibited by either static or dynamic obstacles. These obstacles prevent the direct communication between the vehicles and can craft a situation like non-line of sight (NLOS). This NLOS becomes a perennial problem to the researchers as it creates localization and integrity issues which are considered to be important for road safety applications. Handling the moving obstacles is found to be a challenging one in the VANET environment as obstacles like truck are found to have similar characteristics of the vehicular nodes. This paper utilizes the merits of the meta-heuristic approach and makes use of the improved gray wolf optimization algorithm for improving the localization and integrity services of the VANET by overcoming the NLOS conditions. The proposed methodology is found to have improved neighborhood awareness, reduced latency, improved emergency message delivery rate, and reduced mean square error rate.

KEYWORDS

emergency message, gray wolf algorithm, meta-heuristic, non-line of sight, VANET

1 | INTRODUCTION

In the VANET scenario, the vehicle user pretends to exhibit a delayed reaction even for crisis circumstances, but the drivers must exhibit spontaneous reactions. When the driver tends to exhibit delayed reactions during the communication of disseminating emergency messages, it leads to a crash between the vehicles either emergency or non-emergency vehicles, irrespectively. Due to this delayed reaction of drivers, loss of human life will occur.[1] The major factor behind this delayed action of driver is because of the inappropriate information of a vehicle or the event.[2] The position of the vehicles has to be identified precisely in order to avoid the collision of vehicles in the network. Because of this collision, the emergency vehicles' arrival will get delayed. The probability of collision between the emergency vehicles due to the lack or delayed information is high because the time constraint is very limited for them. In a statistical report of the National Highway Traffic Safety Administration (NHTSA), USA, it is quite evident that nearly 60% of the ambulance accidents occur during the emergency time and the non-emergency vehicles have caused death of almost 56% and majority of the crashes involve multiple vehicles. The majority of the collision occurs at the road intersection between the vehicles because the coverage of the vehicles at this juncture is poor.[3,4]

VANET involves three modes of communication: (i) vehicle to vehicle (V2V), (ii) vehicle to infrastructure (V2I), and (iii) hybrid combination of both (V2V and V2I). The presence of intelligent transport system (ITS) in VANETs has enhanced in providing innovative services regarding traffic management and made the vehicle users better aware of the circumstances and stay connected in the all the situations.[5] In addition, the data dissemination among the vehicles in VANETs does not have a dedicated protocol that will carry the dissemination of messages by minimizing the latency during the transmission.[6,7] Minimizing the latency interns of arrival of emergency messages is found to be a major issue which will minimize the occurrence of vehicle collisions.[8] The data dissemination rate is always influenced by the number of vehicles in the road intersection and also the presence of obstacles[9] it can either be static obstacles such as tall building infrastructures and trees or dynamic obstacles like trees.[10] The dissemination of emergency messages has been greatly affected by the presence of obstacles.[11] The approaching vehicles and the intended vehicles do not share the emergency message within the manipulated time; it will result in collision of vehicles. The presence of obstacle creates a non-line-of-sight (NLOS) situation. Generally multi-hopping mechanism[12,13] can be used if the vehicle is not within the range of communication, but the use of this mechanism creates additional overhead such as retransmission of the messages, and nodes of close range has to be identified for transmission. The presence of NLOS has always been a serious issue, and the NLOS node has to be localized in order to transmit the emergency message. The meta-heuristic approach is identified as an optimal usage in localization and improved gray wolf optimization has been designed.[14] The uniqueness behind using the gray wolf optimization is that it helps in attaining global optimum by exploration and exploitation without getting trapped into local optimum during the search process in identifying the NLOS. When compared to conventional heuristic approaches, the meta-heuristic goes for an extensive search as the search space is not quite known for real time problems. The gray wolf comes under the category of population based as it performs the search process with random initial population, and it is enhanced over the course of iteration. The population based search has benefits such as during the search process, it can move into promising areas of search space and it has greater exploration when compared to single solution based algorithms.

The gray wolf has been designed based on the swarm intelligence behavior of gray wolves in identifying the food prey. The anchor nodes are considered as wolves which encircle the NLOS node whose position has to be identified. The position of the NLOS is subjected to vary during the course of time. The best candidate solution can be obtained from the wolves in identifying the distance between NLOS nodes and the anchor node despite considering the factors of mobility of the vehicles (as the vehicles are found to move at varying speed, it is difficult in predicting the position of the vehicles). The mean square error rate is greatly minimized because of the improved neighborhood awareness rate which helps in the effective localization of the NLOS. This algorithm can be considered as a benchmark on well-known test functions and by comparing with other algorithms like particle swarm optimization, evolutionary programming, evolutionary strategy, and gravitational Search.

The highlights of improved gray wolf optimization is used in localization mainly due to the following:

a. The grey wolf optimization makes use of the anchor node for disseminating emergency message which are not within the transmission range.
b. The major improvement of this approach is minimizing the latency, improving neighborhood awareness rate, and transmission of emergency message by minimizing the delay.
c. The shift in convergence rate is found to be uniformly maintained between the exploration and exploitation.
d. The proposed system is a population based approach in which a better candidate solution can be achieved by moving into optimal areas of search space.
e. The NLOS detection rates 8%, 11%, and 14% are found to be improved when compared to its bench marks CVP, MLVP, and SLA, respectively. There has also been a significant reduction on latency of IGWA in the tune of 4.5%, 8%, and 12% when compared to CVP, MLVP, and SLA approaches. These two metrics are considered more vital during localization of vehicles for which a significant improvement is obtained.

The EstiNet 8.1 tool is used for studying the proposed gray wolf algorithm predominance against the existing schemes.[15] It has the potential of simulating different parameters which is required for road intersection in vehicular networks and different units which is required in the vehicular network can be modeled.

The remainder of the section is organized as follows: Section 2 will discuss the importance of localization, the related works on localizing the NLOS nodes and their pros and cons, and the significance of the outreach of Internet of

Vehicles (IoV) and eminent works in improving the quality of the network in offloading scenarios due to massive resource utilization of devices. Section 3 portrays about the improved gray wolf optimization algorithm for detecting NLOS. Section 4 depicts the simulation setup and experimental results followed by conclusion and references.

2 | RELATED WORKS

This section discusses about the importance of localization, their impacts, and scenarios that perceive into NLOS. As a part of the analysis, the existing methods which are used in identifying the NLOS have been discussed with their merits and demerits.

2.1 | Significance of localization

When vehicles are in the line of sight (LOS), their position, speed, and velocity can be identified. We can calculate the position, speed, and velocity when the vehicles are in LOS. It serves as an input to the approaching emergency vehicles which helps in preventing the vehicles from colliding. If the vehicles are in the NLOS, the position of the vehicles is hard to determine, and eventually, it will result in wrong conclusion of the drivers resulting in fatal accidents. The NLOS generally occurs when there is an interference in the path of communication either by static or dynamic obstacles. NLOS can also be due to the reasons like (1) high density of vehicles, (2) varying speed of the vehicles, and (3) static road way geometry. So effective localization helps in predicting the position of vehicles when the position of the vehicles is hard to predict as direct communication is not possible. The NLOS scenarios may occur during lane merging, intersection of roads, and vehicle moving around the hill. In these scenarios, the communication range between the vehicles is obstructed by either static obstacles like tall buildings and trees present in the road side or moving obstacles like trucks.

The situation which leads to NLOS condition is discussed below:

- Obstacle warning: This scenario arises due to the presence of road side obstacles, where vehicles are slowed down or stopped or are skidding.
- Lane merging: When the vehicles communicate for the purpose of lane change or lane merging, NLOS situation may occur.
- Road intersection: This situation happens in a highway scenario during a road intersection when the vehicles failed to update its information to the approaching vehicles at intersection and due to the presence of road obstacles like road infrastructure or the presence of large vehicles like trucks.
- Roadway condition awareness: During a big turn over a hill, the vehicles have to communicate to the approaching vehicles beyond the LOS.

The subsection below is going to discuss about the eminent methods proposed by the researchers in localizing the nodes in the network.

2.2 | Survey on localization methodologies

Initially, a good number of eminent works has been designed by researchers for effective localization of vehicular nodes. But many of the works were found to have less impact since they are concentrating on the latency on the arrival of emergency messages. Among those methods, significant works has been chosen for the literature review, and a detailed analysis has been made analyzing their merits and demerits.

Initially, Lazos and Poovendran proposed an independent range localization algorithm for identifying the position of the node termed as "HiRLoc."[16] It determines the position without increasing the number of reference points and also the complexity of the hardware. The improved location accuracy of the localization had been achieved as a result of collection of numerous nodes within a short period of time. The major drawback of this approach is that it requires extra directional antennas for the sensor nodes.

The node localization protocols like SeRLoc and ROPE have been proposed by Lazos and Poovendran,[17] and Capkun and Hubaux proposed the SPINE protocol for effective detection of the nodes' position. But the proposed works of Lazos and Poovendran have major drawbacks as it uses extra hardware like sectored antenna for SerLoc and directional antennas for the ROPE protocol.[18] In the case of the SPINE protocol, it creates an overhead since it utilizes more number of beacon messages during the localization process.[19]

Yan et al. provide the node localization approach with the help of onboard radar unit embedded in the OBU of the vehicles.[20] It apparently collects the position of the neighboring vehicles, and it verifies their position coordinates. The position information of the vehicles is determined by the information collected from the radar and the neighboring vehicles. By analyzing the movement of the history of vehicles, the vehicular node packet which is transmitted can be analyzed and the vehicles which send invalid packets can be isolated from the network. The major limitation of this approach is that the LOS is always needed between the vehicles in case the communication of trucks becomes a barrier.

Using the RSSI (Received Signal Strength Indicator), Parker and Valaee localized the position of the vehicular nodes by utilizing the vehicle kinematics, road maps, and distance between the vehicles.[21] Thus, accurate information of the vehicles can be achieved using the RSSI. It is mainly deployed in safety application to avoid a collision. But when this method is subjected to an interference or the presence of obstacles, the position of the target node cannot be determined.

For detecting NLOS node, a trust mechanism has been proposed by Leinmüller et al; this framework is used to identify the cheating nodes who falsify their positions using beacon messages.[22] This approach does not use an additional hardware which is found to be an added advantage, but it uses a sensor to estimate the position of the nodes and analyze its trustworthiness. This sensor is found to run in each node. It incurs computational overhead in analyzing the trustworthiness, and the deployment of the sensor in each node is found to be cost effective.

The concept of usage of Anchor node is been effectively identified Abumansoor et al. for effective emergency message dissemination, therby the NLOS situation can be avoided by the presence of anchor nodes.[23] The use of the cooperative volunteer protocol (CVP) helps in minimizing the delay during the transmission of emergency messages in a timely manner. This CVP NLOS mechanism has been embedded in the on board units for effective localization. It is found to be superior on par with the GRANT protocol proposed by Capkun et al.; this protocol makes use of covert base station, and these Covert Base Stations (CBS) does not reveal the position to attackers.[24] This protocol also has an added advantage that nodes cannot lie about their position pretending to be in different locations. The major drawback of using CBS is that it has to generate a secret key frequently which will act as input for node hiding, but it creates computation overhead and consumption of high energy.

A hybrid real time indoor localization model has been modeled to eradicate the drawbacks faced by using the Received Signal Strength (RSS) for positioning the nodes' location. The drawback faced in RSS is that they have to depend upon nodes for localization, but in the presence of NLOS and if changes in the environment occur, there will be variations in signal propagation. To overcome the drawbacks, Ciabattoni et al. combined RSS and pedestrian dead reckoning for relative positioning of the nodes within a shorter time.[25] This hybrid mechanism is found to have an added advantage that neighborhood awareness is improved, thereby enhancing data transmission.

Qing et al. make use of hyperbolic positioning method for accurate determination of the position of the node by incorporating the location estimation algorithm.[26] This method acquires the essential information using TDOA and provides an exact solution for localization issues. Further, Yin proposed the distance vector hop algorithm which is a range free NLOS method for determining the position of the nodes.[27] It uses volunteer nodes and calculates the single hop distance between the NLOS node and the cooperative node and broadcasts the information and helps in localization.[28]

Abumansoor and Boukerche designed the Multihop Location Verification Protocol (MLVP) which helps in verifying the vehicles which are directly connected when the direct communication between the vehicle is not feasible.[29] The neighboring vehicle helps in verifying the location of the vehicle and transmits the information to the requested verifier. When direct communication fails in retrieving the information of vehicle, the MLVP is triggered and updates the neighborhood list of the vehicles. This mechanism has an added advantage that it provides data integrity of the information exchanged between the neighborhood nodes. The major disadvantage of this approach is that it assumes that at least one vehicle must be in direct communication of the verifier which is practically not feasible all the time.

Secure localization algorithm was proposed by Anjun et al.[30]; it makes use of the nonce mechanism. The source node initially generates nonce packets at different power levels. These packets are transmitted by three reference nodes which are within the communication range. The nonce packet reaches the node which location has to be localized. The nodes receive the nonce and retransmit back to the generated node. Thus, the anchor nodes help in effectively identifying the distance between the reference node and the NLOS. This mechanism is found to be effective only if the nodes are dynamic and in the close proximity range.

The aforementioned drawbacks of the various methods forms the base of formulating the improved gray wolf optimization algorithm and analyzing their merits based on the performance metrics like emergency message delivery rate, neighborhood awareness rate, channel utilization rate, and latency in emergency message delivery against the existing methods chosen.

2.3 | Survey on significance of IoV in VANET

A new era in the field of IoT has evolved which drives the traditional VANETs into IoV. The concept of IoV has been evolving in the recent years as it is an integrated network for sustaining intelligent traffic management, intelligent dynamic information services, and intelligent vehicle control. IoV helps in gathering and sharing of information across vehicles, roads, and its surroundings. In 2024, several auto manufacturers are planning to come up with an ideology to provide platforms that support route management, smart parking, and onboard entertainment centers. The presence of 5G enabled technologies has improved the performance of vehicular networks when compared to the 4G LTE in various safety and infotainment related applications. Since the upcoming period is found to be of 5G enabled communication, the current methodologies used in accessing will face greater setback in rendering the services to the mass connected devices. And also due to the increase in vehicles and asymmetric distribution of traffic flows, it will be vital for the network operators for enhancing the networks performance and to minimize the time variety which is faced in IoV.

So intelligent offloading strategies have been designed and proposed by Ning et al.[31] A mix nonlinear programming has been proposed to minimize the delay faced in the network in terms of network, congestion, and downloading which is faced by the users.[31] Then an online multi-decision making scheme had been proposed to minimize the total network delay. For handling the time varying characteristics of IoV a branch and bound algorithm (B&B) is used which integrates AI and makes use of optimal decisions with minimum training samples. The benchmarks chosen are also quite evident that the improvisation has been obtained when compared to the existing methods. For minimizing the heavy traffic delay faced by the cellular networks, vehicular edge computing is found to be a promising paradigm based on IoV. Wang et al proposed an imitation based online task scheduling algorithm which obtains an optimal performance at the initial stages when compared to other heuristic approaches and machine learning approaches due to its slow convergence rate low searching efficiency.[32] This methodology is found to have a significant improvement than the existing method which is found in the experimental results. And a significant offloading strategy has been proposed by Ning et al. An intelligent offloading framework has been designed for 5G enabled vehicular networks for minimizing the offload costs.[33] So two methods have been proposed for solving the problems of scheduling and allocation in V2R and V2I, namely, unlicensed spectrum, while a distributed DRL-based resource allocation method learning enabled online task. The DRL based conventional method is found to be a centralized approach, and Ning et al. developed a distributed approach which eventually reduces communication overhead. The performance of this methodology is found to be considerably improved than their existing method which is taken for its comparison.

The discussion upon the IoV helps to have a better understanding about the need of the users for supporting various safety related and infotainment applications. The automobile industry has started to move towards IoV as high Quality of Service can be provided by using 5G technology. As, IoV involves in connecting massive devices the concept of offloading helps in minimizing the traffic congestion and network delays that occur buy using the 5G communication. This thrust area has to be improvised as it involves human lives.

3 | OUTLINE ON GRAY WOLF OPTIMIZATION

The meta-heuristic algorithm has grabbed attention in recent times because it is not problem specific. It is designed based on inspiring the natural phenomena especially swarm based algorithms. One such swarm based algorithm was proposed by Mirjalili et al. on inspiring the behavior of a gray wolf. The major reason behind using this behavior is that other swarm intelligence algorithms like ant colony optimization (ACO), bat algorithm (BA), fire fly algorithm, termite algorithm, and cuckoo search algorithm did not adopt the leadership hierarchy and mode of hunting the prey which is present in the gray wolf optimization which is identical when compared to other swarm intelligence algorithms. The phenomenon behavior can be adopted to identify the position of the vehicular nodes which has been obstructed by the obstacle. Identifying the position of the NLOS node plays a vital for preventing fatal accidents resulting in loss of life. The rate of exploration and exploitation can be achieved better when compared with other swarm intelligence algorithms.

Gray wolf algorithms generally live in groups. The gray wolves are classified into four groups as shown in Figure 1 based on the work and responsibility, namely, alpha, beta, delta, and omega. The top hierarchy forms the alpha; they are the leaders, and it includes a male and a female wolf. They are mainly involved in decision making related to hunting and identifying the sleeping place. The alpha's decision has to be followed by the rest of the group. In the group, the alpha wolf is not the strongest but its order has to be obeyed by the rest of the members of the group.

In the pecking order, the next would be the beta wolves, which help the alpha in making better decisions. The beta wolf pack can be either a male or a female. If the alpha category wolf dies or grows older, the next potential candidate to lead the pack will be chosen from the beta category.

The next level in the pecking order in the gray wolves is the omega. It is considered to be the lowest level in the category. Even though they are the last they are not allowed to eat. The omega is even considered as scapegoats, and there is also possible of losing the omega category because of its internal frustration and violence in the omegas.

There is another category called delta which is not in the actual list, but they tend to dominate the omega and they report only to the alpha and beta. This category of gray wolves will perform the work of hunting, securing boundaries, and will intimate to alpha in case of danger is found to pertain in the borders, and it also includes elderly wolves which will place the role in alpha, and they are also the care takers of the wounded wolves. An identical behavior of the gray wolves is the group hunting. It involves three phases during hunting: (1) tracking phase, (2) encircling phase, and (3) attacking the target.

3.1 | Mathematical modeling of weighted gray wolf optimization mechanism in NLOS detection

The meta-heuristic approach generally does the search in two phases one is the exploration and another is the exploitation. A global search is generally made during the exploration phase in identifying the promising search areas in a random fashion and during the exploitation phase the local search is done in the promising areas which is identified as a part of exploration. This objective has been applied in identifying the position of the unknown NLOS node by using exploration and exploitation phases.

Initially, the vehicular nodes are present in a terrain of "R*R" and "N" be the number of vehicular nodes present in the terrain. Initially, the anchor nodes have been arbitrated from any point of the network depending on the presence of the NLOS node. If the search space is found to be large i.e the distance between the NLOS node and the anchor node the rate of exploration has to be increased. If the best promising search space of the NLOS is identified then exploitation is carried out and the position of the NLOS is identified.

The finest candidate solution can be considered from the alpha group, and the second and third candidate solutions that can be taken into consideration will be the beta and delta. The last candidate solution taken for consideration can be the omega.

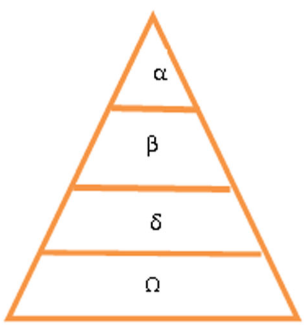


FIGURE 1 Hierarchy of gray wolves

3.2 | Encompassing stage

As discussed in a previous section, the first phase of the hunting is the encompassing stage. In this stage, the gray wolves surround the prey, and wolves can be related to the anchor vehicular nodes, and the prey can be referred as the NLOS vehicular node which the position must be identified. The encompassing behavior of the gray wolves is depicted using Equation 1.

$$\vec{D} = \left| \vec{C}.\vec{X}_{NLOS}(t) - \vec{X}(t) \right|, \tag{1}$$

where t indicates the specified period of time which is the current iteration. But during the course of encircling the iteration will be increased to identify the position of the NLOS node (Prey) which is determined with the Gray wolf (Anchor node) which is obtained using Equation 2.

$$\vec{X}(t+1) = \vec{X}_{NLOS}(t) - \vec{A}.\vec{D}. \tag{2}$$

$\vec{X}_{NLOS}$ represents the current position of the NLOS node and $\vec{X}$ indicates the current position of the anchor node. The best search agent can be obtained by altering the position of $\vec{A}$ and $\vec{C}$.

$\vec{A}$ and $\vec{C}$ are determined using Equations 3 and 4.

$$\vec{A} = 2\vec{d}.\vec{n}_1 - \vec{d}, \tag{3}$$

$$\vec{C} = 2.\vec{n}_2. \tag{4}$$

$\vec{d}$ has been linearly decreased from 2 to 0 during the iteration process and $\vec{n}_1$ and $\vec{n}_2$ are random vectors in the range of 0 to 1. Let us consider the scenario that the position of the gray wolf (anchor node) will be in the coordinates (M, N), and it can update the position with respect to the prey (NLOS node) which is considered to be in the coordinate (M_1, N_1). The best agent can be obtained by altering the $\vec{A}$ and $\vec{C}$ vectors. The anchor node updates its position inside the encircling space where the NLOS node is present using Equations 1 and 2.

3.3 | Tracking phase

The gray wolves initially have the ability to recognize the prey and encircle them. The hunting is carried by the alpha wolves (anchor node), but in an intangible search space, it is difficult to exactly figure out the position of the NLOS node. So it is wiser to consider the other wolves; namely, beta, delta, and omega are considered as anchor nodes; it will possibly update its position with respect to the NLOS node. It has been considered that the best solution is always obtained from the alpha (A_α), beta (A_β), and delta (A_δ).

$$D_{A_\alpha} = \left| \vec{C}_1.\vec{X}_{A_\alpha} - \vec{X} \right|, \tag{5}$$

$$D_{A_\beta} = \left| \vec{C}_2.\vec{X}_{A_\beta} - \vec{X} \right|, \tag{6}$$

$$D_{A_\delta} = \left| \vec{C}_3.\vec{X}_{A_\delta} - \vec{X} \right|, \tag{7}$$

$$\vec{X}_1 = \vec{X}_{A_\alpha} - \vec{A}_1.\left(\vec{D}_\alpha\right), \tag{8}$$

$$\vec{X}_2 = \vec{X}_{A_\beta} - \vec{A}_2.\left(\vec{D}_\beta\right), \tag{9}$$

$$\vec{X}_3 = \vec{X}_{A_\delta} - \vec{A}_3.\left(\vec{D}_\delta\right), \tag{10}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}. \tag{11}$$

Using Equations 5–11, the best solution is obtained to identify the position of the NLOS node with the help of the alpha (A_α), beta (A_β), and delta (A_δ). The omega (A_Ω) also updates its position randomly around the prey.

3.4 | Attacking phase

This phase is the exploitation phase where the best candidate solution is obtained with respect to the NLOS node. The NLOS node is better determined when the value of $\vec{d}$ and $\vec{A}$ is decreased. The value of $\vec{d}$ will be minimized from the range 2 to 0 during the process of iteration. And the value of $\vec{A}$ will take between the range of −1 to 1. The next position of the anchor node will be in the range between the current position of the anchor node and the determined NLOS node for better localization.

3.5 | Searching phase

This phase is the exploration phase where the search process for determining the position of the NLOS is initiated with the help of anchor nodes (gray wolves) alpha (A_α), beta (A_β), and delta (A_δ). Each anchor node updates its candidate solution with respect to the prey. The vector $\vec{d}$ is minimized from 2 to 0 to support exploration and exploitation. The candidate solution will diverge when $\left|\vec{A}\right| > 1$ and tend to converge when the value is $\left|\vec{A}\right| < 1$. The value of $\vec{C}$ should provide random values each time during the iteration process during the initial and final iterations. The $\vec{C}$ plays a major role in tacking the obstacle like trucks in the vehicular environment. The $\vec{C}$ does it by assigning weight for the anchor nodes and helps in identifying the position of the NLOS nodes.

4 | EXPERIMENTAL RESULTS AND ANALYSIS

The improved gray wolf algorithm is investigated using EstiNet 8.1. It is the commercial version of the NCTUns network simulator and emulator, and it has more than 20,000 registered users across more than 165 countries.[34] The EstiNet 8.1 has been developed by adopting the merits of NCTUns 6.0 and eradicating the demerits. The EstiNet 8.1 has important features like IEEE 802.11p VANET emulator and IEEE 802.11n that supports network simulations. The improved gray wolf algorithm has been deployed in the network to analyze the performance with a maximum of 200 vehicular nodes, and the nodes are distributed in the terrain of 2500 m × 2500 m. The other environmental factors utilized for the creation of network has been discussed in Table 1. The improved gray wolf algorithm is investigated based on the neighborhood awareness rate, latency, emergency message delivery rate, and mean square error rate under node density of the network. Subsequently, the proposed work is also investigated against the neighborhood awareness rate, latency, emergency message delivery rate, and mean square error rate under varied anchor nodes.

In Table 1, the simulation parameters used in analyzing the performance of the gray wolf algorithm has been discussed.

Figures 2 and 3 depict the emergency message delivery rate, and the neighborhood awareness of IGWA is analyzed based on the increasing number of vehicular nodes. The emergency message delivery rate is found to be dominant when compared to the existing mechanism MLVP-NLOS, CVP-NLOS, and SLA-NLOS by 22.8%, 28.5%, and 33%. The emergency message delivery rate is found to be a significant factor in identifying the position of the vehicles, either emergency or non-emergency vehicles, to avoid collisions. Likewise, the neighborhood awareness of IGWA is found to be dominant when compared to the MLVP-NLOS, CVP-NLOS, and SLA-NLOS methods. The neighborhood awareness

TABLE 1 Simulation parameters used in analyzing the performance of the gray wolf algorithm

The parameters used for simulation	Values
Area of simulation	2500 m × 2500 m
Time of simulation	300 s
Range of transmission	250 m
Bandwidth used	12 mbps
Maximum speed of vehicles	40 m/h and 80 m/h
Size of warning messages	512 bytes
Type of traffic	Constant bit rate (CBR)
Type of MAC protocol	IEEE 802.11p
Maximum number of vehicles	200
Type of mobility generator	OpenStreetMap

FIGURE 2 IGWA emergency message delivery rate

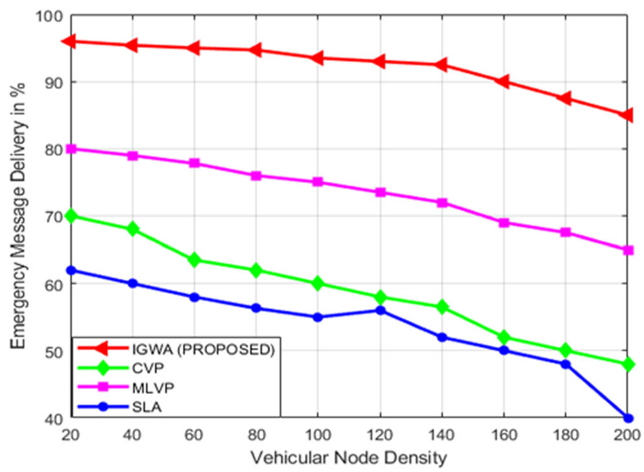
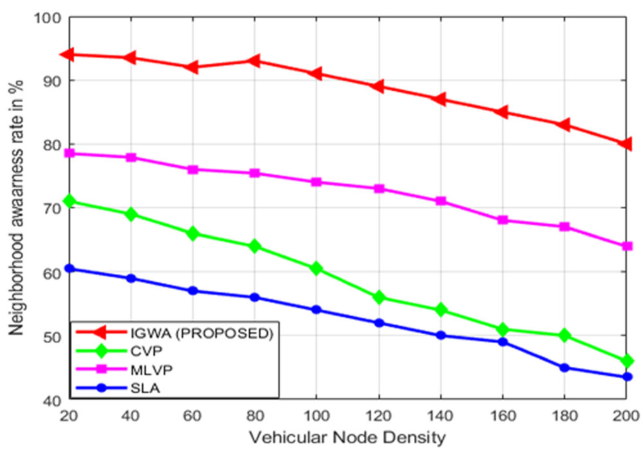


FIGURE 3 IGWA neighborhood awareness rate



rate plays a major role in identifying the position of the nodes as it helps in grabbing information from the neighboring vehicles for the detection of NLOS nodes. Thus, the neighborhood awareness rate is improved by 26.5%, 30%, and 34% compared to the MLVP-NLOS, CVP-NLOS, and SLA-NLOS methods.

Figures 4 and 5 highlight the efficiency of IGWA with MLVP-NLOS, CVP-NLOS, and SLA-NLOS using latency in delivering the emergency message and mean square error rate. The latency in delivering the emergency message is considerably reduced by the presence of volunteer nodes or the anchor nodes which aid in identifying the position of the NLOS nodes. The mean square error is significantly minimized between the actual and possible position for localizing the position of NLOS nodes. Hence, the latency is found to be minimized by 22%, 24%, and 27% when compared to

MLVP-NLOS, CVP-NLOS, and SLA-NLOS. The mean square error rate in minimizing the error approximation in calculating the distance between the NLOS and the anchor nodes is minimized by 21%, 25%, and 29% when compared to MLVP-NLOS, CVP-NLOS, and SLA-NLOS.

Figures 6 and 7 reveal the performance of IGWA based on the performance of emergency message delivery rate and neighborhood awareness rate when estimated under increasing number of volunteer nodes. The emergency message delivery rate is highly influenced based on the rising number anchor nodes as the distance between the NLOS node and anchor node is normalized highly when compared to the existing works. Thus, the warning message delivery rate is found to be better by 22%, 25.5%, and 28% with existing works MLVP-NLOS, CVP-NLOS, and SLA-NLOS. The neighborhood awareness rate is found to be improved by increasing the number of volunteer nodes as the distance between

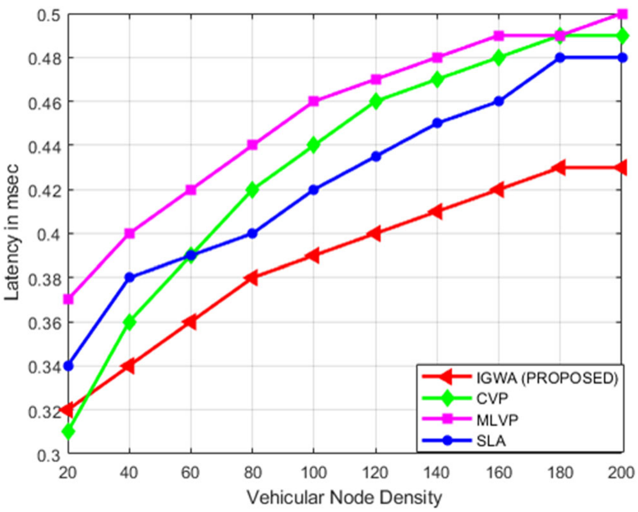


FIGURE 4 IGWA latency in emergency message delivery

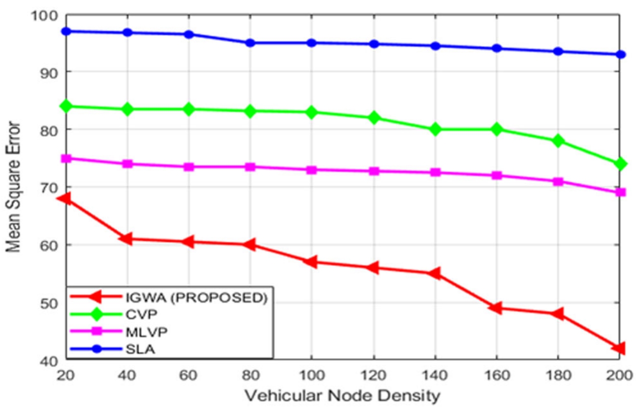


FIGURE 5 IGWA mean square error rate

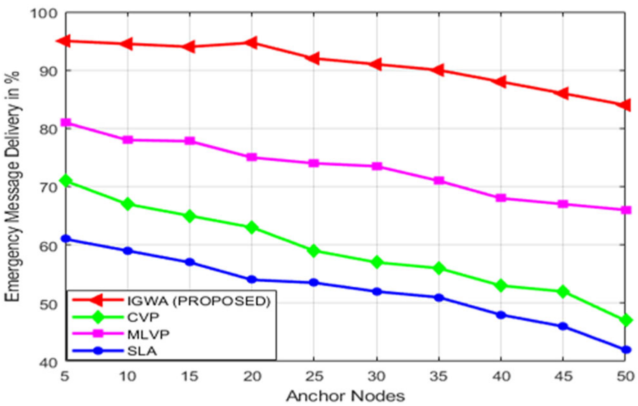


FIGURE 6 IGWA emergency message delivery rate based on anchoring nodes

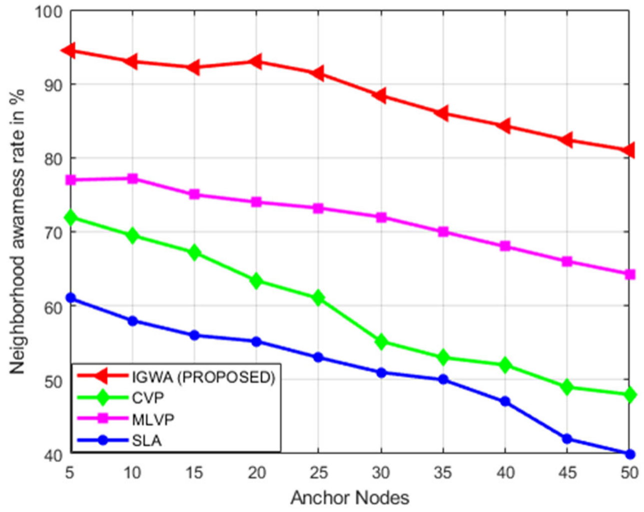


FIGURE 7 IGWA neighborhood awareness rate based on anchor nodes

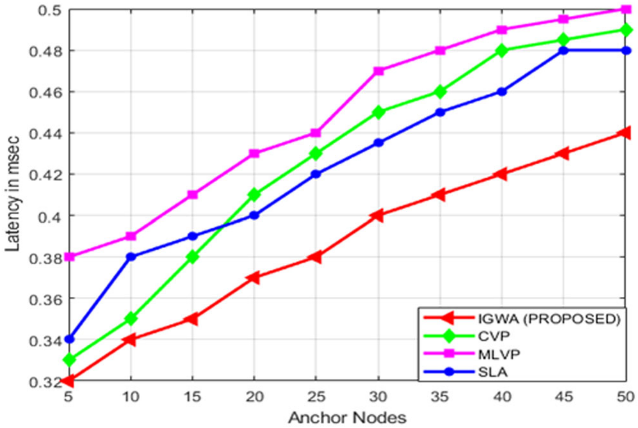


FIGURE 8 IGWA latency based on anchor nodes

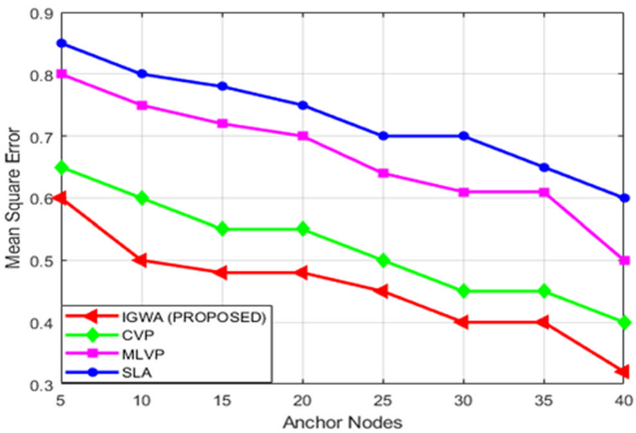


FIGURE 9 IGWA mean square error based on anchor nodes

the NLOS and volunteer nodes is considerably reduced because of the increased number of anchor nodes. Thus, the neighborhood awareness rate is found to improve by 15%, 18%, and 22% when compared to the baseline methods MLVP-NLOS, CVP-NLOS, and SLA-NLOS.

In the next part of the analysis, Figures 8 and 9 depict the latency and mean square error which have been studied under varied number of anchor nodes. The mean square error is found to be a key factor for localization as it minimizes the error between actual and estimated distance which is calculated between the NLOS and anchor nodes. The mean square error is found to be significantly minimized when IGWA is against the baseline MLVP-NLOS, CVP-NLOS, and SLA-NLOS by 22%, 24%, and 27%. The latency of IGWA which is investigated is found to minimize by 23%, 26%, and

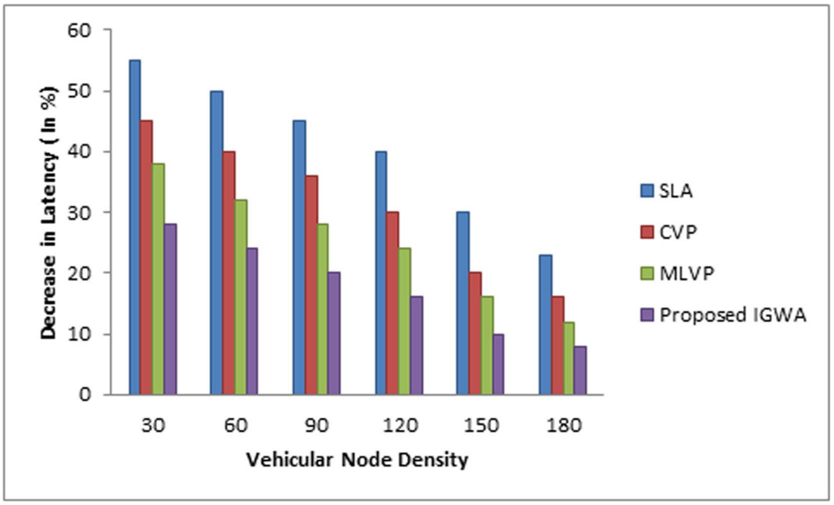


FIGURE 10 IGWA decrease in latency against vehicular node density

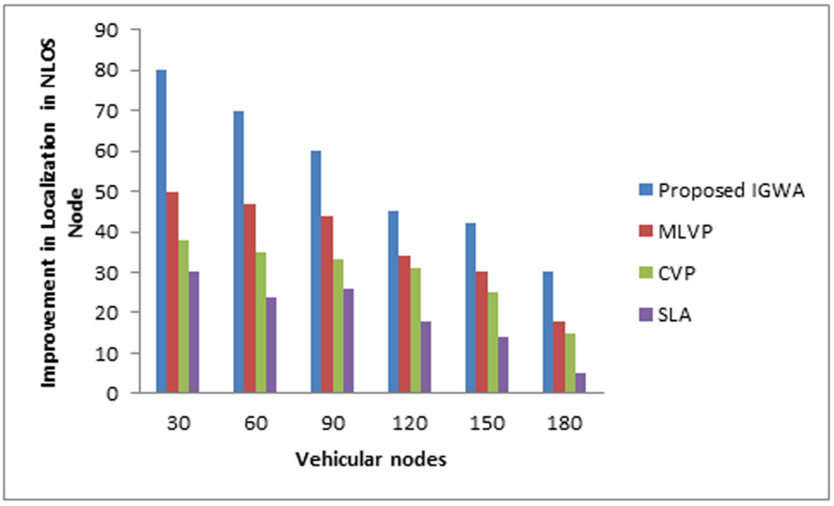


FIGURE 11 IGWA NLOS localization rate against vehicular node density

30%. The latency is a major factor in delivering the emergency message within the stipulated time. The presence of latency has been considerably minimized by IGWA due to benefits of the meta-heuristic approach.

In Figure 10, it elevates the performance of IGWA over MLVP-NLOS, CVP-NLOS, and SLA-NLOS when compared against increased number of vehicles in the network. The minimization in the latency which is observed in IGWA is due the increased control in the exploitation phase in identifying the position ofthe NLOS node. The latency of the proposed IGWA is found to be minimized by 4.5%, 8%, and 12% when compared to the bench mark chosen. In Figure 11 it highlights how IGWA helps in better localization even in increased number of vehicular nodes when compared against MLVP-NLOS, CVP-NLOS and SLA-NLOS. The proposed IQWA helps in better localization even under increased number of vehicular nodes. As the overhead which is incurred in delivering the emergency messages is been minimized which is observed from the results obtained. The NLOS detection rate is found to be improved by 8%, 11%, and 14% when compared to its baseline MLVP-NLOS, CVP-NLOS, and SLA-NLOS.

5 | CONCLUSION

NLOS nodes in VANET are a huge cause of concern which had to be resolved. The proposed IGWA clearly shows there is a decrease in latency which was caused due to the transferring of data among the nodes that are available in VANETs. The proposed system IGWA utilizes the benefits of the meta-heuristic approach. The proposed methodology resolves the pointless exploration and exploitation which was found to be one of the major concerns that pertained the existing system which were explained in the literature survey. When compared to the existing systems like CVP, MLVP, and SLA, there has been a significant improvement in the NLOS detection rate 8%, 11%, and 14%, respectively. There has also been a significant reduction on latency of IGWA in the tune of 4.5%, 8%, and 12% when compared to CVP, MLVP, and SLA approaches. In the future, this methodology could be integrated with several other swarm intelligence approaches for aiding better localization.

Data sharing not applicable to this article as no datasets.

ORCID

Ramu Kaviarasan https://orcid.org/0000-0003-2010-6446
Pillutla Harikrishna https://orcid.org/0000-0002-7301-2366

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