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A Hybrid Crow Search and Gray Wolf Optimization Algorithm-based Reliable Non-Line-of-Sight Node Positioning Scheme for Vehicular Ad hoc Networks

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Summary

Vehicular Ad hoc NETwork (VANET) facilitates ubiquitous connectivity for establishing Vehicle-to-Vehicle (V2V) communication and supporting Intelligent Transportation Systems (ITSs). This vehicle communication requires complete coverage within the target range for ensuring reliable message dissemination. High density of vehicles in the intersections introduces challenges due to obstacles such as buildings, foliage, and other moving vehicles, preventing exchange of information about location and message update between vehicles. Non-Line-of-Sight (NLOS) nodes also introduce broadcasting storm problem leading to congestion that prevents emergency messages from reaching the target vehicular nodes. Integration of meta-heuristic Crow Search Algorithm (CSA) and Gray Wolf Optimization Algorithm (GWOA) minimizes the objective function of NLOS localization problem without the solution being trapped into local optima. In this paper, a Hybrid Crow Search and GWOA-based NLOS Positioning Scheme (HCSGWOA-NLOS-PS) is proposed to handle the issue of broadcast storm and facilitate reliability in emergency message delivery. The proposed HCSGWOA-NLOS-PS utilizes the benefits of Time of Arrival (ToA) and geographical information-based cooperative localization agent for attaining efficient NLOS node positioning in the network. It uses the benefits of CSA and GWOA for positioning the NLOS nodes based on the intelligence derived from the crows' conduit and the social attacking behavior of gray wolves that are ideal for balancing the tradeoff between exploration and exploitation. The simulation results of the proposed HCSGWOA-NLOS-PS confirm a mean emergency message delivery of 11.82%, neighborhood awareness of 12.38% with reduced localization error rate of 2.36% and minimized delay of 8.64% when compared to the baseline approaches.

KEYWORDS

Crow Search Optimization Algorithm (CSOA), Gray Wolf Optimization Algorithm (GWOA), NLOS positioning, Non-Line-of-Sight (NLOS) nodes, Vehicular Ad hoc NETworks (VANETs)

1 | INTRODUCTION

From the recent past, Intelligent Transportation System (ITS) uses Vehicular Ad hoc NETwork (VANET) as the most potential technology to achieve the objective of interconnecting vehicles, roads and people. This interconnection between vehicles is achieved through Global Navigation Satellite System (GNSS), Geographic Information System (GIS) and Global Position System (GPS). The ITS applications are categorized into three types namely, information service, traffic efficiency and road safety.[1] VANET facilitates real-time communication based on Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) for implementing the applications of information service, traffic efficiency and road safety through ITS. In specific, V2V communication of VANET only requires On-Board Units (OBUs) for implementation.[2] On the other hand, V2I necessitates Road Side Units (RSUs) that are extremely expensive and hence is highly limited in number especially in suburban areas. In this context, V2V is determined to be more suitable than V2I.[3] The state of congestion introduced by the data generated from the applications of ITS has the maximum probability of incurring a huge delay in end-to-end packet delivery with drastic packet loss. Traditionally, the data generated in the network is categorized into emergency messages that are time-critical and ordinary data that are insensitive in nature.[4] The time-critical emergency messages are to be propagated into the network and should reach the target vehicle with reduced delay before data timestamp expiry.

Emergency message delivery in urgent situations such as road accidents, road construction and road damages needs to be rapidly exchanged or disseminated to the target police and ambulance vehicles for responsive action.[5] However, the major challenge involved in emergency message dissemination completely focuses on the process of minimizing the time period incurred in transmission. This time period in the process of warning message dissemination is the difference between the time of commencement of the emergency situation and the delivery of warning message to the neighboring vehicular nodes.[6] This time period plays an indispensable role in reducing the degree of collision and channel contention in the network. The sustenance of network coverage among the vehicular nodes that lie within the targeted communication range of data dissemination is another challenge. The high vehicular density at road intersections is already challenging.[7] Furthermore, foliage, tall buildings and other vehicles can also act as obstacles in the process of transmitting warning message from emergency vehicles to the target police or ambulance vehicles.[8] The aforementioned challenges emphasize the necessity of conducting continuous research for identifying the number of obstacles that hinder the transmission of emergency messages.[9] The obstacles should be determined for ultimately minimizing the number of collisions with a view to ensure timely message reception at the target vehicles and rapid decision process by the drivers of the source vehicle for reactive response in stimulus to the emergency event.[10] Moreover, the vehicular nodes with different dimensional speeds and compositions can contribute to the additional Non-Line-of-Sight (NLOS) situations.[11] These NLOS nodes can be intentional or non-intentional but greatly influence the degree of communication with the view to update location information among neighboring vehicular nodes for positioning.[12] It can affect the information sharing process and lead to fatal accidents that hinder the process of updating parameters related to location, direction and speed of vehicles.[13] Thus, the existence of NLOS nodes in the network further increases the challenge of positioning them in order to maximize the possibility of time-critical data dissemination between the source and target vehicles under emergency situations.[14] The problem of positioning NLOS nodes for transmitting time-critical messages from the accidental vehicle to the ambulance or police vehicle during the process of emergency message delivery is considered as a non-linear NP problem.[15]

Meta-heuristic algorithms are considered to be suitable for handling the problem of NP that concentrates on the localization of NLOS nodes in the network. But utilization of standalone meta-heuristic algorithm for localization either fails in the process of intensification or diversification during the NLOS position estimation based on the known location of the neighboring nodes. This limitation of standalone algorithms is mainly identified to be resolved during mutual integration of a superior intensification algorithm with equally potential diversification algorithm. This kind of integration of global and local optimal algorithms aids in balancing the deviation between intensification and diversification. At this juncture, the hybridization of meta-heuristic schemes such as Ant Colony Optimization (ACO), Artificial Bee Colony (ABC) optimization, ElephantHherd Optimization (EHO) algorithm and Binary Bat Optimization (BBO) algorithms are considered to be better algorithms that could be possibly integrated for sustaining the balance between intensification and diversification. They are also determined to be identified to be highly suitable for positioning NLOS nodes in the network by preventing the solution from falling into local optima.

In addition, the possibility of hybridizing Crow Search Optimization Algorithm (CSOA) and Gray Wolf Optimization Algorithm (GWOA) contributed by Arora et al.[16] and Subramanian et al.[17] motivated the option of incorporating them for effective and reliable positioning of NLOS nodes in the network and ensuring a high degree of warning message delivery with balanced tradeoff between exploration and exploitation. In specific, GWOA is developed with the leadership properties and distinct hunting capability of gray wolves. This GWOA is considered to prevent local optimal stagnation to a considerable extent. It is also considered to possess good convergence potential towards the point of optimality. Thus, it is confirmed that it is potentially strong in exploitation, but not exploration. On the other hand, GWO cannot handle the problem successfully and fails in determining the global optimal solution. On the other hand, Crow Search Algorithm (CSA) is a meta-heuristic algorithm proposed with the intelligent characteristic of crows. This CSA has the ability of preventing local optima with more efficiency, when handling with high dimensional problems of NLOS node localization. It is not very significant in the local search strategy. Thus, integration of GWOA and CSA is essential in order to achieve maximized convergence rate and solution accuracy. In addition, Figure 1 presents the workflow of the integrated CSOA and GWOA towards NLOS positioning.

Motivated by the aforementioned points, Hybrid Crow Search and GWOA-based NLOS Positioning Scheme (HCSGWOA-NLOS-PS) is proposed with balanced exploitation and exploration for accurate localization of NLOS nodes to prevent broadcast storm in order to ensure reliability in emergency message delivery. The proposed HCSGWOA-NLOS-PS uses the strategy of cooperative positioning by recovering the location of vehicles based on vehicular nodes' relative range measurement and GNSS information. This localization scheme integrates the merits of CSOA such as modified position update, Non-Linear Control Parameter (NLCP) inclusion, and adaptive balance probabilistic strategy into the search mechanism of GWOA for sustaining the balance between exploration and exploitation by reactively and mutually resolving the limitations of each algorithm. In particular, the modified position update of CSA aids in better balance in searching process, NLCP inclusion aids in preventing the fall of solution into local point of optimality, and adaptive balance probabilistic strategy supports in accelerating the process of searching the position of NLOS with known position of neighborhood vehicular nodes. The simulation of this proposed HCSGWOA-NLOS-PS is conducted using EstiNet 8.1 simulator for determining its predominant performance over the benchmarked NLOS schemes in terms of localization error rate, channel utilization rate, packet latency, neighboring vehicle awareness degree- and warning message delivery rate independent of the number of vehicles, reference nodes and NLOS nodes in the network.

The remaining sections of the paper are organized as follows. Section 2 presents the related work of existing state-of-art approaches propounded in the literature for NLOS nodes localization in vehicular nodes. Section 3 details the primitives of CSA and GWOA and the process of integrating them for potential NLOS localization process with the need for integration. Section 4 demonstrates the simulation results of the proposed HCSGWOA-NLOS-PS evaluated based on the delivery rate of warning message, mean processing rate of request verification, rate of awareness, end-to-end delay, channel utilization, rate of localization and localization error with different vehicle densities, NLOS

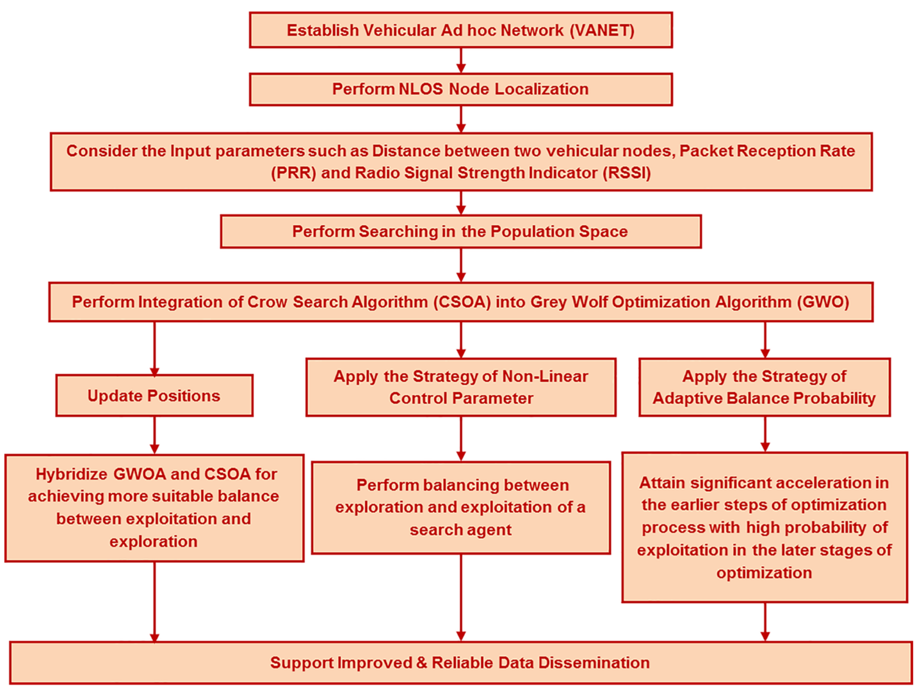

FIGURE 1 Workflow of the Integrated CSOA and GWOA towards NLOS Positioning

nodes, reference nodes and elapsed time of simulation in the network. Section 5 concludes the paper with contributions and future scope of enhancement.

2 | RELATED WORK

An NLOS node verification scheme is proposed for cooperative positioning with the objective to ensure maximum degree of secure location services during emergency situations.[18] This cooperative positioning scheme helps in provisioning reliability and maintaining service and integrity during the process of localization in urgent situations. The degree of localization error, incurred delay and neighborhood awareness degree achieved by NLOS node verification scheme is determined to be significant when compared to the Time of Arrival (ToA) information-based schemes existing in the literature. A fuzzy logic-based NLOS node positioning scheme is proposed for securing reliability and integrity under trust establishment among vehicular nodes.[19] This NLOS localization scheme based on the aspect of plausibility and experience executes a series of security checks for ensuring the information correctness received from trusted vehicles. This fuzzy logic-based NLOS identification scheme is capable even when imprecise, incomplete and inaccurate information is exchanged between vehicles. It is independent of the stationary and mobile obstacles that introduce interference in vehicular communication. It is potent in detecting faulty and attacker nodes and prevents imprecision and uncertainty in sharing warning messages in Line-of-Sight (LOS) and NLOS situations.

A NLOS node verification technique for handling spoofing attack in urgent contexts of vehicular networks is proposed for improving the rate of data dissemination in ITS applications.[20] This NLOS positioning scheme includes a challenge and response approach of claiming the positions of vehicular nodes and estimating the correct location based on the geographic information derived from geographical information systems. It incorporates the merits of both range and range-free positioning technique for effective location identification of nodes in NLOS situations. The rate of localization error and time incurred for localization are identified to be highly minimized independent of the number of vehicular and reference nodes in the network. Cooperative Volunteer Nodes-based NLOS node Positioning Scheme (CVN-NLOS-PS) is proposed for accurate identification of hidden nodes that increases the rate of warning message transmission with highly reduced delay.[21] CVN-NLOS-PS is a reliable technique that completely concentrates on handling the problem of channel contention and broadcasting storm. It is implemented as a significant approach propounded for exchanging warning messages from emergency source vehicles to the unidentified NLOS nodes and increasing the rate of packet delivery, ensuring effective channel utilization with minimized packet latency and communication overhead. This NLOS positioning scheme includes specially designated vehicular nodes named volunteer nodes for ensuring reliable data dissemination among vehicular nodes in NLOS situations. It also presents the role of OBU entities and the importance of their cooperation in data collection and making decisions based on data sensing.

A NLOS node positioning scheme based on the merits of Weighted Distance Hyperbolic Prediction (WDHP-NLOS-PS) is proposed for determining the location of vehicular nodes in NLOS situations.[22] This NLOS positioning scheme includes the benefits of range-free algorithms for forecasting the dynamic positions of vehicular nodes derived from the characteristics of hyperbolic trajectory. The WDHP-NLOS-PS scheme is proposed for preventing channel contention and broadcasting storm that results in enhanced channel utilization, neighbor awareness degree and warning message exchanging rate independent of the densities of vehicular and NLOS nodes in the network. Further, Weighted Inertia-based NLOS Positioning Scheme with the benefits of Dynamic Virtual Bat Algorithm (WI-NLOSPS-DVBA) is also proposed for resolving the issue of channel contention and broadcasting storm in vehicular networks.[23] The proposed WI-NLOSPS-DVBA scheme inherits the merits of Particle Swarm Optimization (PSO) and Simulated Annealing (SA) with an objective of accurate NLOS node positioning. In particular, the advantages of WI are incorporated into the traditional dynamic virtual binary algorithm for preventing the issue of premature convergence. The exploitation and exploration involved in the process of NLOS localization are reactively increased or decreased based on the relative position of the vehicular node in the network. This scheme is also confirmed to improve the rate of warning message delivery, neighboring node awareness and reduce the packet latency in the vehicular network. Cooperative positioning scheme based on GNSS estimators is proposed for effective determination of NLOS nodes under emergency situations.[24] This GNSS estimator-based positioning scheme resolves the issue of channel contention and broadcasting storm. It is proposed to prevent increased retransmissions of warning messages. It is a significant approach for accurate estimation of NLOS nodes such that warning messages are always delivered to the target vehicle for ensuring reactive response in urgent situations.

A Centroid Scheme for NLOS Localization based on the merits of Criteria Improved Confidence (CS-NLOSL-CIC) is proposed for resolving the issue of channel contention and broadcasting storm in the vehicular network.[25] This CS-NLOSL-CIC approach includes two vital factors such as penalty cost and primitive cost for computing the value of the integrated cost that plays a vital role in constructing the confidence. This measure of confidence is used for judging the rank which is systematically improved based on the gradient methods in the perturbation process. This CS-NLOSL-CIC approach is determined to enhance the rate of warning message delivery, neighboring node awareness and reduce the packet latency in the vehicular network to an acceptable degree. A reliable data exchange approach using resilient traffic services is proposed for transmitting the predicted data based on the inclusion of fuzzy aggregation approach.[26] This data exchange approach includes the integration of cloud layer with VANET for achieving potential network performance and enhancing safety of the data traffic even in the scenario of congestion. This fuzzy aggregation scheme incorporates the benefits of the connected sensor network for the purpose of gathering data traffic information that helps the cloud infrastructure to facilitate better demand and reactive cloud services. The evaluation phase of this data exchange approach confirms its improvement in network performance and traffic safety compared to the baseline schemes considered for investigation. A cuckoo filter-based trust model with the merits of vehicular type, experience and plausibility is proposed for enhancing security under NLOS conditions.[27] This trust model is proposed as a reliable approach for handling network issues that emerge due to LoS and NLOS nodes that include uncertainty, incomplete and inaccurate data. It uses k-nearest neighbor classification algorithm based on the properties of symmetry and feature similarity with an objective of detecting NLOS conditions. It estimates the distance between two vehicular nodes, with Packet Reception Rate (PRR) and Radio Signal Strength Indicator (RSSI) as the input features of the incorporated classification algorithm. It also includes the cuckoo filter for facilitating secure communication between the edge and the vehicle node during the generation and propagation of big data. This trust model is identified to improve the overall accuracy, recall and precision with decreased communication overhead. It is proved to handle different types of attacks such as cunning attack, opinion tampering and simple attack compared to the weighted voting and attack-resistant trust management schemes.

A mean bit error rate-based reliable routing algorithm is proposed as an adaptive routing scheme with the benefits of Nakagami-m fading channel for forecasting link quality under NLOS conditions.[28] This reliable routing algorithm computes the remaining battery energy for the purpose of energy efficient routing and prolonging network lifetime. It includes the measure of Canberra distance rather than a measure of Euclidean distance for enhancing the prediction accuracy involved in distance measurements. It also forecasts and maintains superior optimal path in order to determine and sustain a consistent path with enhanced QoS in real-time scenarios. A novel bearing and coordinate localization scheme is proposed for predicting the position of NLOS nodes with hierarchical tracking process.[29] This node bearing scheme is proposed for sensing and communicating data among the neighbors for achieving local sensing process. It is proposed for sustaining connectivity by adapting to the changes in the network topology for regaining the communication path. It is also determined to be highly fault tolerant even in the presence of rogue nodes in the vehicular network.

2.1 | Extract of the Literature

In this section, the shortcomings identified from the state-of-art approaches proposed in the literature (Table 1) over the recent years[30-31] are presented.

1. Most of the existing schemes of the literature still have the possibility of improving the tradeoff between the exploitation and exploration in the process of localization.
2. The majority of the standalone meta-heuristic localization schemes have limitations either in the process of local or global search.
3. The accuracy level of prediction included by the existing approaches during the localization process has the maximum probability of improvement.

3 | PROPOSED HCSGWOA-NLOS-PS

The proposed Hybrid Crow Search and Grey Wolf Optimization Algorithm-based NLOS Positioning Scheme (HCSGWOA-NLOS-PS) is a reliable attempt to position NLOS nodes in the network by integrating the merits of CSOA

TABLE 1 Comparison of the state-of-art reviewed NLOS localization schemes

Authors	Mechanism	Merits	Demerits
Abumansoor and Boukerche[18]	Multi-Hop Location Verification Protocol (MHLVP)	• Provides reliability for maintaining service and integrity during localization in urgent situations • Significant in reducing localization error, delay and neighborhood awareness degree	• Provides less support for preventing contention with maximised accuracy
Soleymani et al.[19]	Secure trust model based on fuzzy logic	• Offers reliability and integrity under trust establishment among vehicular nodes • Efficient even when imprecise, incomplete and inaccurate information are exchanged between vehicles	• Localization can still be improved with increase in the vehicular density
Zubairu[20]	MHLVP for mitigating spoofing attacks	• It is a range-free positioning technique for effective location identification of nodes in NLOS situations • Ensures minimized rate of localization error and time incurred for localization independent of the number of vehicular and reference nodes	• Works only with maximized number of reference nodes • Incurs huge amount of delay
Alodadi et al.[21]	Cooperative Volunteer Nodes-based NLOS node Positioning Scheme (CVN-NLOS-PS)	• Offers accurate identification of hidden nodes that increases the rate of warning message transmission with highly reduced delay • Ensures reliable data dissemination among vehicular nodes in NLOS situations	• Facilitates localization with maximized error • Involves more degree of channel contention during deployment
Amuthan and Kaviarasan[22]	Weighted Distance Hyperbolic Prediction based NLOS node Positioning Scheme (WDHP-NLOS-PS)	• Includes range-free algorithms for forecasting the dynamic positions of nodes • Yields better channel utilization, neighbor awareness degree and warning message exchanging rate independent of the densities of vehicular networks	• Found to be insignificant when the number of obstacles increase in the network • Determined to incur some degree of localization error
Amuthan and Kaviarasan[23]	Weighted Inertia-based NLOS Positioning Scheme with Dynamic Virtual Bat Algorithm (WI-NLOSPS-DVBA)	• Inherits merits of Particle Swarm Optimization (PSO) and Simulated Annealing (SA) • Incorporates the merits of Weighted Inertia (WI) into the traditional dynamic virtual binary algorithm for preventing premature convergence	• The degrees of exploitation and exploration are considered to still have a room of improvement
Lassoued and Bonnifait[24]	Cooperative localization for autonomous vehicles sharing GNSS measurements	• Prevents the possibility of retransmissions during the transmission of warning messages • Facilitates accurate estimation of NLOS nodes	• Incapable of handling the obstacles that contribute towards NLOS situation in the network
Amuthan and Kaviarasan[25]	Centroid Scheme for NLOS Localization based on the merits of Criteria Improved Confidence (CS-NLOSL-CIC)	• Offers enhanced rate of warning message delivery and neighboring node awareness • Reduces packet latency in the network to an acceptable degree	• The degree of exploitation and exploration are considered to still have a room of improvement • Demands improvement of the accuracy level in node localization

(Continues)

TABLE 1 (Continued)

Authors	Mechanism	Merits	Demerits
Abdelatif et al.[26]	VANET-cloud architecture for traffic management	• Achieves potential network performance and enhances safety of data traffic even during congestion • Facilitates better demand and reactive cloud services on demand	• The degrees of exploitation and exploration are considered to still have a room of improvement. • Demands improvement in the accuracy level of localization • Necessitates predominant reduction of latency in warning message delivery
Soleymani et al.[27]	Cuckoo filter-based trust model (F-trust)	• Reliable for handling network issues emerging due to LOS and NLOS nodes including uncertainty, incomplete and inaccurate data • Handles cunning attack, opinion tampering and simple attack	• Involves high localization error • Supports low uncertainty handling
Sivasubramanian and Subramaniam[28]	Adaptive Routing Scheme (ARS) considers the algorithm Reliable Routing (RR)	• Enhances the prediction accuracy in distance measurements • Forecasts and maintains superior optimal path to determine and sustain a consistent path with enhanced QoS in real-time scenarios	• Offers less possibility of contention reduction • Involves high communication overhead for positioning the unknown NLOS nodes
Kim[29]	Non-Line-of-Sight error mitigating algorithms for transmitter localization based on hybrid TOA/RSSI measurements	• Sustains connectivity for adapting to changes in the network topology for regaining the communication path • Offers high fault tolerant, even in the presence of rogue nodes in the vehicular network	• Incapable of handling all the obstacles that contribute towards NLOS situation in the network

into GWOA. This integration is performed to circumvent channel contention and broadcast storm and thereby sustain the delivery of warning messages in emergency situations without packet delay. It includes the strategies of position updation, Adaptive Balance Probability (AB_{Prob}) and NLCP for efficient positioning of NLOS nodes in the vehicular network. In this section, the basic description of the traditional GWOA and CSOA are presented for understanding their pros and cons. Then, the process of integrating GWOA with CSOA and their role in the efficient positioning of NLOS nodes in the vehicular network is explained through algorithm and flowchart.

3.1 | Classical GWOA

This classical GWOA was introduced by Mirjalili et al.[32] as one of the significant mechanisms in the field of nature-inspired meta-heuristic approaches propounded in the literature in the recent years. This GWOA is contributed by mimicking the hunting and leadership qualities of socially behaving gray wolves. These gray wolves represent a class of Canidae family that follows a restricted and well-disciplined social hierarchy. They always hunt their prey in groups by self-organizing themselves as a pack of 5–12. This pack of gray wolves is designated into four levels of hierarchy, namely, Alpha, Beta, Delta and Omega wolves. An Alpha wolf may be a male or a female but lies at the first level of the hierarchy as it is the leader of the entire pack. It completely takes the role of decision making related to the patterns of behavior associated with hunting, waking time, sleeping time and maintaining discipline in the complete pack. Beta wolves lie in the second level of the hierarchy in GWOA, and they play the role of subordinates to the Alpha wolves by cooperating with them in decision making and other related tasks that need to be carried out in the process of establishing social behavior. These Beta wolves have the maximum possibility of being selected as Alpha wolves in succession to lead the entire pack on the death of the present Alpha wolves. The Delta wolves lie in the third level of hierarchy and are responsible for coordinating between the Beta and Omega wolves. The Mega wolves play an anchor role in sustaining safety and integrity among the members of the complete pack. The main four phases of the traditional GWOA are detailed below.

3.1.1 | Process of Prey Encircling (NLOS encircling)

GWOA is mathematically modeled using the social hierarchy of gray wolves (localizing agent) that are categorized into Alpha, Beta, Delta and Omega wolves (agents) for facilitating better cooperation to position NLOS nodes. The mathematical equations used in GWOA for encircling the prey (NLOS nodes) based on reference nodes are represented in Equations 1 and 2.

$$\overrightarrow{P_E} = \overrightarrow{R_{V(A)}}\left(\overrightarrow{V_{P(NLOS)}}(t) - \overrightarrow{V_{P(WA)}}(t)\right) \tag{1}$$

$$\overrightarrow{V_{P(NLOS)}}(t+1) = \overrightarrow{V_{P(NLOS)}}(t) - \overrightarrow{R_{V(B)}}.\overrightarrow{P_E} \tag{2}$$

where '$\overrightarrow{V_{P(WA)}}$' and '$\overrightarrow{V_{P(NLOS)}}$' represent the position vector corresponding to wolf agents and the unknown NLOS nodes at any time instant 't'. '$\overrightarrow{P_E}$' is the predicted distance between the wolf agents (reference nodes) and the prey (NLOS nodes). Moreover, '$\overrightarrow{R_{V(A)}}$' and '$\overrightarrow{R_{V(B)}}$' are the random vectors that are calculated based on Equations 3 and 4 respectively.

$$\overrightarrow{R_{V(A)}} = 2\,\overrightarrow{v_c}.\overrightarrow{r_a} - \overrightarrow{v_c} \tag{3}$$

$$\overrightarrow{R_{V(B)}} = 2\,\overrightarrow{r_b} \tag{4}$$

At this juncture, '$\overrightarrow{v_c}$' is used as the control vector for calculating the first random vector '$\overrightarrow{R_{V(A)}}$' and controlling the behavior of GWOA towards prey encircling (NLOS positioning). The component values over the course of iterations decrease linearly from 2 to 0. Further, '$\overrightarrow{r_a}$' and '$\overrightarrow{r_b}$' help the wolf agents to estimate any point between the reference node and the unknown NLOS nodes. These random vectors lie between 0 and 1.

3.1.2 | Hunting Prey Phase in GWO

The GWOA is capable of predicting the location of the prey and the positions of NLOS nodes (whose locations are unknown) such that their positions can be potentially determined and encircled (localized). It is potent in updating the location of the reference nodes in the network that takes action to move towards the position of the unknown NLOS nodes with the help of Alpha, Beta and Delta wolf agents (movement modeling) based on Equations 5–11 respectively.

$$\overrightarrow{P_{E(\propto)}} = \left| \vec{R}_{V(B1)} . \vec{V}_{P(WA\bar{\propto})} - \vec{V}_{P(NLOS)} \right| \tag{5}$$

$$\overrightarrow{P_{E(\beta)}} = \left| \vec{R}_{V(B2)} . \vec{V}_{P(WA\bar{\beta})} - \vec{V}_{P(NLOS)} \right| \tag{6}$$

$$\overrightarrow{P_{E(\delta)}} = \left| \vec{R}_{V(B3)} . \vec{V}_{P(WA\bar{\delta})} - \vec{V}_{P(NLOS)} \right| \tag{7}$$

$$\vec{V}_{P(NLOS\bar{\propto})}(t+1) = \vec{V}_{P(NLOS\bar{\propto})}(t) - \vec{R}_{V(B1)} . \vec{P}_{E(\propto)} \tag{8}$$

$$\vec{V}_{P(NLOS\bar{\beta})}(t+1) = \vec{V}_{P(NLOS\bar{\beta})}(t) - \vec{R}_{V(B2)} . \vec{P}_{E(\beta)} \tag{9}$$

$$\vec{V}_{P(NLOS\bar{\delta})}(t+1) = \vec{V}_{P(NLOS\bar{\delta})}(t) - \vec{R}_{V(B3)} . \vec{P}_{E(\delta)} \tag{10}$$

$$\vec{V}_{P(NLOS)}(t+1) = \left(\frac{\vec{V}_{P(NLOS\bar{\propto})}(t) + \vec{V}_{P(NLOS\bar{\beta})}(t) + \vec{V}_{P(NLOS\bar{\delta})}(t)}{3} \right) \tag{11}$$

Further, the process of searching process is updated in the memory as described below.

3.1.3 | Process of Searching and Attacking Prey in GWO

In general, the gray wolves (search agent) attack the prey (explore the search population), until it stops moving (the search solutions does not change). This characteristic of gray wolves (search agent) is mathematically modeled based on the primitive vector '$\vec{v}_c$' represented in Equation 3. The random vector is considered to range between $[-\vec{v}_c, \vec{v}_c]$ with its value decreased from 2 to 0 for varying number of iterations based on Equation 12.

$$\vec{v}_c = 2 - \left(2 * \frac{t}{Max_{Iter_{COUNT}}} \right) \tag{12}$$

In this context, if '$\vec{v}_c < 1$', then the search agents focus on the exploitation over the search space. In contrast, if '$\left|\vec{v}_c\right| > 1$', then the search agents concentrate on the exploration for effective positioning of NLOS node with the aid of reference nodes. This process of positioning unknown NLOS nodes is thus achieved based on the utilization of Alpha, Beta, and Delta wolf search agents.

3.2 | Steps Involved in CSOA

The steps involved in the implementation of the CSOA[33] are explained as follows:

Step 1: In this step, the decision variables and the constraints that influence the optimization problem associated with NLOS node positioning based on reference nodes are identified. The values of adaptive factors such as

Awareness Probability (A_P), Maximum Iteration Count ($Max\_\ Iter_{COUNT}$), Flock Size (F_{Size}), and Flight Length (F_{Length}) used in the optimization problem of positioning NLOS nodes are also initialized.

Step 2: A two-dimensional (2D) matrix of size, '$F_{Size} \times N_{Dec-var}$' is constructed, where 'F_{Size}' and '$N_{Dec-var}$' pertain to the number of crows (reference nodes used for positioning NLOS nodes) and the number of decision variables (dynamic variables which contribute towards effective localization process).

Step 3: Fitness value of the optimization problem is determined based on the distance between the reference nodes and the unknown NLOS nodes, energy possessed by the reference nodes towards localization, current location and predicted position of the NLOS nodes.

Step 4: In this step, the new location of the crow (reference nodes) is initially determined.[34] Then, the awareness probability 'A_P' initialized in the first step is compared with the newly generated random number in order to estimate its proximity with the reference and NLOS nodes. If the value of awareness probability 'A_P' is identified to be greater than the newly generated random number, then the crow search agent (reference node) is selected based on the probability by estimating the fitness function that determines the positioning of the NLOS nodes in the search space (vehicular network). Else, the search agent 'C^j ' randomly selects the crow (reference nodes) from any crow flock 'C^{f}' (cluster of reference nodes). This search agent is also responsible for tracking 'C^f with the view of predicting the position of the NLOS nodes. Thus, the new locations of the NLOS nodes based on reference nodes are predicted based on Equation 13.

$$C^{i+1,t+1} = C^{i,t} + rn_i * FL^{i,t}_{Length} * \left(C^{f,t} - C^{i,t}\right) \tag{13}$$

where 't' and 'rn_i' refer to the iteration count and a random number generated during the positioning of NLOS nodes, respectively.

Step 5: In this potential step, the fitness value of the vehicular node being positioned is computed as shown in Equation 9.

Step 6: The fitness value of the NLOS vehicular nodes in the newly updated position and its old position is compared. If the newly updated location of NLOS nodes is accurate, then the new predicted position is updated in the memory for successive iterations.

Step 7: The aforementioned Steps 4–6 are iterated until the termination conditions are satisfied or the maximum iteration count is met.

3.3 | Integration Process of CSOA into GWOA

The GWO algorithm as a standalone algorithm is capable of preventing local optimal point stagnation to a maximum level. It also possesses superior convergence potential in reaching the global optimal solution. However, the guarantee in implementing complete exploration is not feasible in GWOA. In some specific cases, it may not always handle the optimization problem successfully and may fail to determine the global optimum solution. On the other hand, CSOA is proficient in effortlessly preventing the local point of optimality when dealing with a high dimensional problem like the NLOS node positioning problem. But the local search mechanism of CSOA is not highly efficient. Hence, GWOA and CSOA mutually have limitations in global and local search strategies, respectively. Thus, it is necessary to integrate a significant global exploration strategy inherent in CSOA into GWOA and incorporate the efficient local search capability of GWOA into CSOA to maintain a tradeoff between exploitation and exploration involved in positioning the NLOS nodes.

3.3.1 | Modified Position Updation Mechanism

In the classical GWOA, the primitive objective is to focus on the mechanism of updating the position of the search agents (reference nodes) based on the cooperation of the first level search agents (Alpha wolves), secondary search agents (Beta wolves), and tertiary search agents (Delta wolves) as highlighted in Equation 11. But this process of position updating might completely end in premature convergence. This limitation of GWOA is mainly due to the prevention of search agents from exploring the complete search space. The process of optimization presented in Equation 11 only enables restricted capabilities in exploitation. But it has the maximum probability in ending with slow convergence during the final stages of optimization. Hence, the major limitation of the traditional GWOA should be prevented by integrating it with the CSOA. To be specific, CSOA is integrated with GWOA by utilizing a control parameter named Flock Length (LT_{FL}). The Flock length (LT_{FL}) is used for updating the positions of the search agents as demonstrated in Equation 13. It plays a vital role in allowing the search agents to realize the extent to which the reference nodes can predict the position of the unknown NLOS nodes. This control parameter is potent in attaining the superior global point of optimality in exploration and excellent local optimal point of exploitation. The search process (local and global search) can be contracted or expanded based on the value of flock length with respect to the required searching process. As stated earlier, GWOA is superior in exploitation but inferior in exploration. Hence, Flock length (LT_{FL}) is used for improving the degree of exploration in GWOA through CSOA as shown in Equation 14. In short, the proposed HCSGWOA-NLOS-PS is predominant in maximizing the advantages of GWOA and CSOA algorithms for achieving universal applicability and suitability in a strengthened way. The search agent is allowed to update the position of the vehicular nodes based on the information determined from the Alpha and Beta search agents rather than utilizing the complete search agents (Alpha, Beta, and Delta) as portrayed in Equation 14.

$$V_{P(WA)}(t+1) = V_{P(WA)}(t) + LT_{FL} * Rand * \left(\left(V_{P(WA-\alpha)} - V_{P(NLOS)} \right) + \frac{\left(V_{P(WA-\beta)} - V_{P(NLOS)} \right)}{2} \right) \tag{14}$$

Further, the search solutions (unknown NLOS nodes) in the population (network) are not updated by the direction or control of Alpha and Beta search agents. Only the Alpha agent is permitted to control the search solutions in the proposed HCSGWOA-NLOS-PS based on Equation 15.

$$V_{P(WA)}(t+1) = V_{P(WA)}(t) + LT_{FL} * Rand * \left(V_{P(WA-\in)} - V_{P(NLOS)} \right) \tag{15}$$

This equation is the significant addition, since it acts as a reliable shrinking methodology for facilitating the proposed scheme to escape from the local point of optimality.

3.3.2 | Strategy of Adaptive Balance Probability

In spite of the predominant potentialities of exploitation and exploration in the proposed scheme, an effective balance between the two steps needs to be achieved in attaining superior performance. The algorithm should offer maximum capability of exploring the large search space in the earlier stage of optimization to prevent premature convergence. At the same time, it must be potent in exploiting precise regions in the later part of the optimization for effectively refining the final search solutions. Hence, the fixed balance probability established between Equations 14 and 15 are not preferable for achieving the necessitated ratio of exploitation and exploration. At this point, a flexible parameter termed as Adaptive Balance Probability (AB_{Prob}) is essential in the proposed scheme for facilitating complete acceleration throughout the earlier phases of optimization with later phases of optimization deriving promising solutions that possess maximum probabilities under exploitation. The aforementioned 'AB_{Prob}' is computed using Equation 16.

$$AB_{Prob} = 1 - \left(\frac{1.01 * t^3}{(Max + Iter)_{COUNT}} \right) \tag{16}$$

In specific, 'AB_{Prob}' completely depends on '$\vec{v}_c$' which plays an ultimate role in controlling the search process direction. Higher values of '$\vec{v}_c$' aid in achieving exploration, while smaller values of '$\vec{v}_c$' play a key role in exploitation.

3.3.3 | Strategy of NLCP

An appropriate selection of vector '$\vec{v_c}$' is potent in balancing the rate of exploitation and exploration which in turn leads to predominant performance. The value of the vector '$\vec{v_c}$' is monotonically decreased from 2 towards 0 based on Equation 3. The different mechanisms[16,35,36] proposed in the literature for updating the control vector '$\vec{v_c}$' prove that the predominant performance of the optimization process is achieved, only when its value is selected through a non-linearly decreasing methodology rather than a linearly decreasing strategy. Thus, an enhanced methodology is included in generating the control vector '$\vec{v_c}$' value in the process of optimization as demonstrated in Equation 17.

$$\vec{v_c} = 2 - (\text{cosine}(\text{Rand}()) * \frac{1}{(\text{Max} + \text{Iter})_{\text{COUNT}}} \tag{17}$$

The aforementioned strategy of utilizing nonlinearly decreasing methodology in selecting and updating the control vector '$\vec{v_c}$' facilitates the maximum option of effectively exploring the search space on par with the standalone GWO algorithm.

In the forthcoming section, the flow chart (Figure 2) and algorithm of the proposed HCSGWOA-NLOS-PS are presented.

Algorithm of the proposed HCSGWOA-NLOS-PS:

Step 1: Initialize and deploy the complete population of vehicular nodes at random positions in the network

Step 2: Set the parameters '$\vec{v_c}$', '$\overrightarrow{R_{V(A)}}$', and '$\overrightarrow{R_{V(B)}}$' required for achieving GWO-based NLOS positioning process

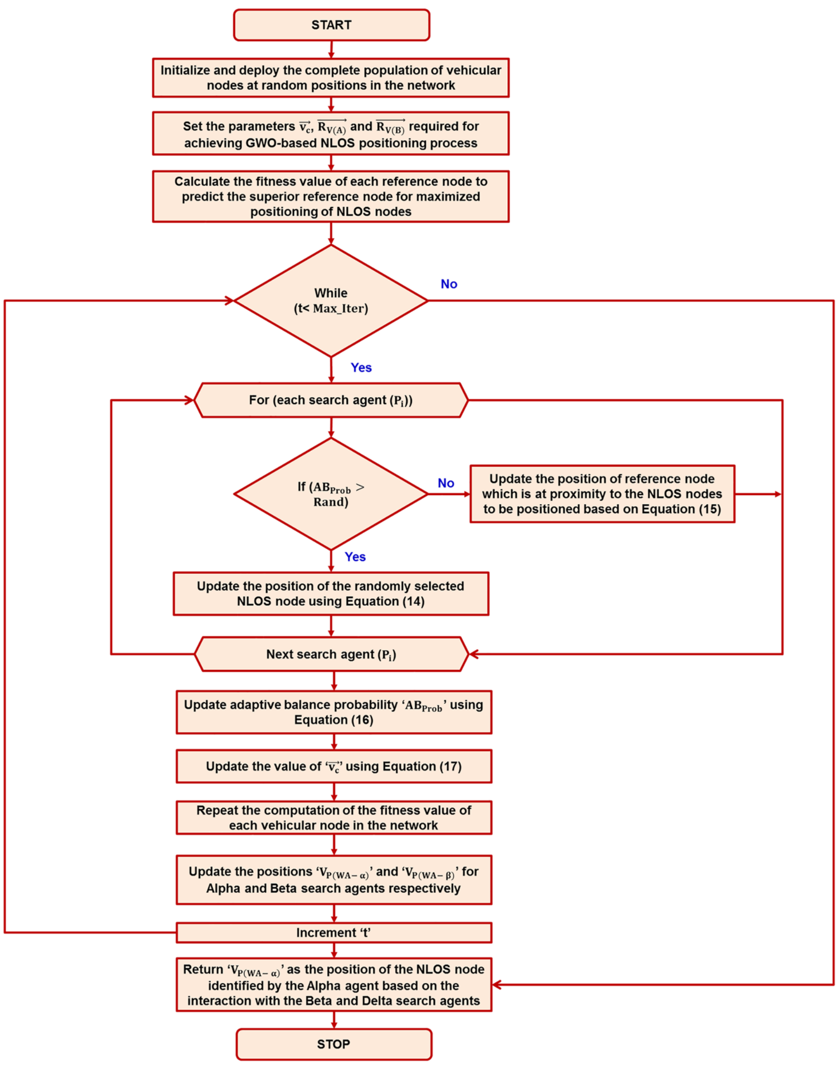

FIGURE 2 Flowchart of the proposed HCSGWOA-NLOS-PS

Step 3: Calculate the fitness value of each reference node to predict the superior reference node for maximized positioning of NLOS nodes
Step 4: Repeat the following steps until 't' is less than 'Max_ Iter'
Step 4.1: For every vehicular node in the network, if 'AB_{Prob}' is greater than 'Rand', then update the position of the randomly selected NLOS node using Equation 14. Else update the position of reference node which is at proximity to the NLOS nodes to be positioned based on Equation 15.
Step 4.2: Update 'AB_{Prob}' using Equation 16
Step 4.3: Update the value of '$\vec{V_c}$' using Equation 17

Step 4.4: Repeat computation of the fitness value of each vehicular node in the network
Step 4.5: Update the positions '$V_{P(WA-\alpha)}$' and '$V_{P(WA-\beta)}$' determined in the network that play a key role of Alpha and Beta Search agents, respectively
Step 4.6: Increment 't'
Step 5: Return '$V_{P(WA-\alpha)}$' as the position of the NLOS node identified by the Alpha agent based on the interaction with the Beta and Delta search agents

The aforementioned algorithm is explained as follows. Initially, the vehicles considered in the search space are positioned at different positions in the network. The positions of vehicles and their lower and upper velocities of movement are also set. Then, the fitness value (using vehicular nodes' relative range measurement and GNSS information of each reference node) for predicting the exact location of reference node for suitable positioning of NLOS nodes is computed. In this context, if the value of vehicular 'AB_{Prob}' is greater than 'Rand,' then the position of the randomly selected NLOS node is updated. Otherwise, the position of reference node based on strategy of NLCP is updated. After every iteration, if the positions of the vehicles do not change, then the same solution is retained. Otherwise, the fitness of reference nodes for predicting NLOS nodes based on 'AB_{Prob}' is recomputed. Finally, the position of NLOS nodes based on reference nodes prediction is predicted.

4 | SIMULATION RESULTS AND DISCUSSION

The simulation experiments of the proposed HCSGWOA-NLOS-PS and the benchmarked approaches are conducted and validated using EstiNet 8.1 Simulator.[37–44] The simulation parameters considered for implementing the proposed HCSGWOA-NLOS-PS and the benchmarked WI-CLOSPS-DVBA,[23] CS-NLOSSL-CIC,[25] WDHP-NLOS-PS,[22] and CVN-NLOS-PS[21] schemes are kept constant throughout the simulation.[17,45–49] They are implemented with the same environment, traffic condition and mobility model. The complete simulation experiments of the proposed HCSGWOA-NLOS-PS and the benchmarked schemes are conducted for a network of size 1500 × 1500 m with 500 vehicular nodes deployed in the network. IEEE 802.11p is used as the MAC layer protocol with a frequency of 5.89 GHz. OpenStreetMap mobility generator is used in this simulation.[50–55] Evaluation parameters such as the delivery rate of warning message, mean processing rate of request verification, rate of awareness, end-to-end delay, channel utilization, rate of localization and percentage of localization error are determined for different vehicle densities, number of NLOS and reference nodes and elapsed time for quantifying the potential of the proposed scheme as a significant NLOS positioning scheme as suggested in previous studies.[23–25,45,46] Enhanced weight-based clustering algorithms are used for pointing the region in the network.[50,56–60] Fourfold cross validation is used during the prediction process. The completion simulation is run 100 times and the average of the results is considered as the resultant performance. In addition, the simulation parameters considered for implementing the proposed HCSGWOA-NLOS-PS and the baseline approaches taken for comparison are presented in Table 2.

The evaluation parameters considered for evaluating the proposed HCSGWOA-NLOS-PS are defined[27] below:

- Warning message delivery rate: It is the cumulative number of packets successfully delivered to the destination node, including the packets routed among the intermediate vehicular node for the purpose of reaching the destination. The objective of this metric concentrates on the process of determining the efficacy of the routing approaches with respect to successful delivery of packets.
- Overhead: It is the total number of control packets generated during the process of data transmission in order to initiate the process of successful data delivery to the destination vehicular node.

TABLE 2 Simulation Parameters for the Implementation of the Proposed HCSGWOA-NLOS-PS

Simulation parameters	Value used for simulation
Number of vehicular nodes	500
MAC layer protocol	IEEE 802.11p
Range of transmission	200 m
Maximum simulation time	500 s
Warning packet size	512 bytes
Minimum speed of vehicular node	30 mph
Maximum speed of vehicular node	70 mph
Bandwidth	12 Mbps
Area of simulation	15,000 × 1500 square meters
Transmission rate	6 Mbits/s
Mobility generator	OpenStreetMap
Vehicles traffic per hour	1000 vehicles per hour
Pattern of communication	Vehicle-to-vehicle communication
Transmission frequency	10 Hz
Scenario considered for NLOS localization	Semi-urban and urban
Probability of awareness	0.1
Flight length	2
Nonlinear control parameter (NLCP)	2 to 0

- End-to-end delay: It is the measure of the essential time delay incurred for forwarding data packet from the source vehicular node to the destination vehicular node, including the time incurred for processing data during the operations of buffering and retransmission.
- Neighbor awareness and location verification: It is the measure used for evaluating the performance of the proposed approaches contributed in detecting vehicles under NLOS and identifying the location through the incorporation of cooperative schemes. It is the measure through which the source node detects possible number of vehicles in the surrounding that are highly matching with the requirements of their range of communication. This metric is highly essential in NLOS contexts where failures of packet delivery to the interacting vehicles are possible due to the presence of obstacles. It can also be defined as the potential of the proposed NLOS node detection approach in successfully detecting the NLOS situations in the network.
- Channel utilization: It is the measure used for evaluating the scalability and efficacy of the proposed cooperative NLOS node detection approaches utilized for the transmission of packets to the destination nodes. This metric also quantifies the predominance of the proposed cooperative NLOS node detection approaches with respect to the number of messages generated and capacity of channel occupied by them.
- Response time: It is the time incurred from the request generated from the sender vehicular node to the reception of reply packets from other vehicular nodes of the network during the existence of NLOS conditions in emergency scenarios.

The simulation results of the proposed HCSGWOA-NLOS-PS are investigated in four different folds. In the first fold of investigation, the proposed HCSGWOA-NLOS-PS is compared with the benchmarked schemes in terms of delivery rate of warning message, mean processing rate of request verification, rate of awareness, end-to-end delay, channel utilization, rate of localization and localization error for different vehicle densities in the network. In the second fold of investigation, the proposed HCSGWOA-NLOS-PS is further compared with the benchmarked schemes based on delivery rate of warning message, rate of awareness and localization error for varying number of NLOS nodes in the vehicular network. In the third fold of analysis, the proposed HCSGWOA-NLOS-PS is explored based on the delivery rate of warning messages, rate of localization and localization time for increasing number of reference nodes considered for positioning. In the final fold of investigation, the proposed HCSGWOA-NLOS-PS is investigated in terms of rate of awareness, end-to-end delay and channel utilization for different elapsed times of simulation.

4.1 | Results of Simulation Experiments Conducted based on Varying Vehicle Densities

In this section, the proposed scheme is compared with the benchmarked schemes based on the delivery rates of warning messages, mean processing rates of request verifications, rate of awareness, end-to-end delay, channel utilization, rate of localization and localization error with different neighborhood vehicle densities in the network. This investigation is conducted with 100 NLOS nodes, simulation time of 500 s and 40 reference nodes which are taken as constants.

Figures 3 and 4 present the delivery rate of warning messages and mean processing rates of request verification achieved by the proposed HCSGWOA-NLOS-PS when compared to the benchmarked schemes taken for investigation. The proposed HCSGWOA-NLOS-PS is realized to improve the delivery rate of warning messages and at the same time reduce the mean processing rate of request verification. This predominant capability is mainly due to the prevention of premature convergence of GWO integrated with GWOA. It aids in balancing the probability step which is adaptively estimated based on the number of vehicle densities on the network. The delivery rate of warning messages achieved by the proposed HCSGWOA-NLOS-PS for different neighborhood vehicular densities on the network is identified to be 8.42%, 9.79%, 12.84% and 14.12% better when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis. The rate of awareness facilitated by the proposed HCSGWOA-NLOS-PS for varying number of neighborhood vehicular densities in the network is also concluded to be considerably reduced by 9.16%, 10.68%, 11.94% and 11.58% in contrast to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes considered for analysis.

Figures 5 and 6 highlight the rate of awareness and end-to-end delay involved in the implementation of the proposed HCSGWOA-NLOS-PS and the benchmarked schemes under the influence of different neighborhood vehicular densities in the network. The proposed HCSGWOA-NLOS-PS offers an enhanced rate of awareness of neighboring vehicular nodes and minimized degree of end-to-end delay independent of the neighborhood vehicular densities in the network. This potential is mainly due to the incorporation of the NLCP inherently used with CSOA for facilitating possible improvement into GWOA. It improves its local positioning capability even under dynamic increase in vehicular

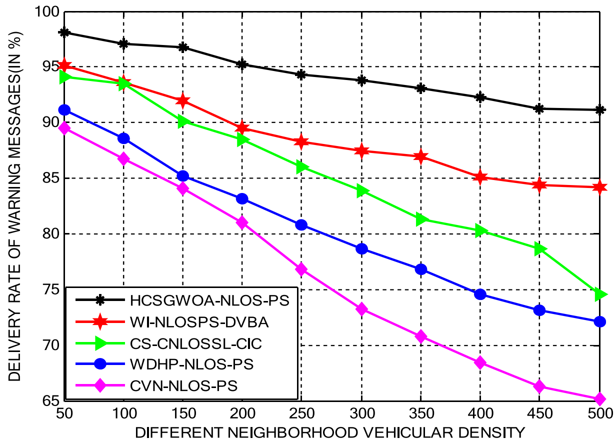

FIGURE 3 Delivery Rate of Warning Messages of the Proposed HCSGWOA-NLOS-PS for Varying Vehicle Densities

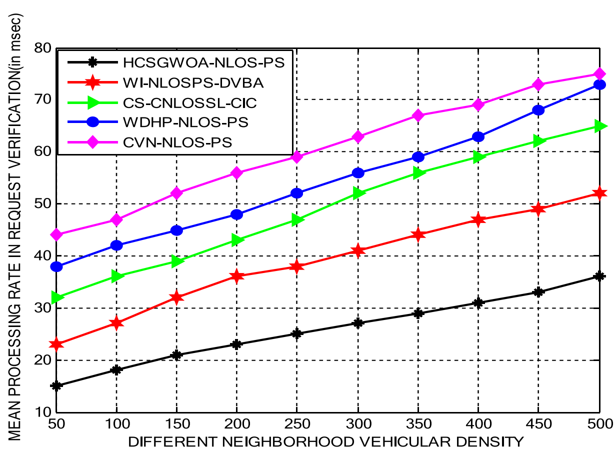

FIGURE 4 Mean Processing Rate of Request Verification of the Proposed HCSGWOA-NLOS-PS for Varying Vehicle Densities

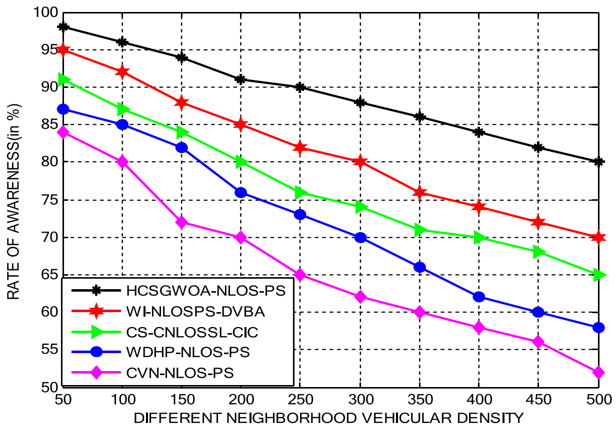

FIGURE 5 Rate of Awareness of the Proposed HCSGWOA-NLOS-PS for Varying Vehicle Densities

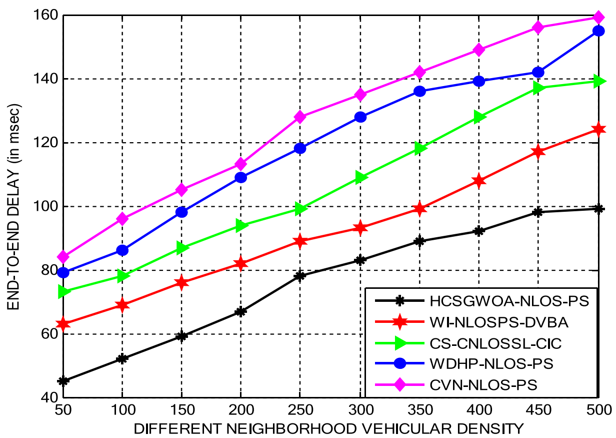

FIGURE 6 End-to-end Delay of the Proposed HCSGWOA-NLOS-PS for Varying Vehicle Densities

nodes in the network. The rate of awareness of the proposed HCSGWOA-NLOS-PS with a corresponding increase in neighborhood vehicular densities is identified to be significant by 9.14%, 11.18%, 12.84% and 13.94% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes considered for analysis. The end-to-end delay attained by the proposed HCSGWOA-NLOS-PS with a corresponding increase in neighborhood vehicular densities is also confirmed to be excellently reduced by 9.42%, 11.42%, 13.85% and 15.28% in contrast to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes considered for analysis.

Figures 7 and 8 portray the rate of localization and localization error achieved by the proposed HCSGWOA-NLOS-PS and the benchmarked schemes for varying neighborhood vehicular densities in the network. The proposed

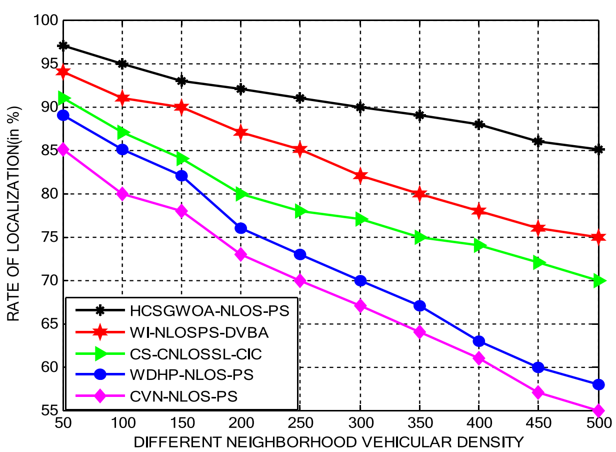

FIGURE 7 Rate of Localization of the Proposed HCSGWOA-NLOS-PS for Varying Vehicle Densities

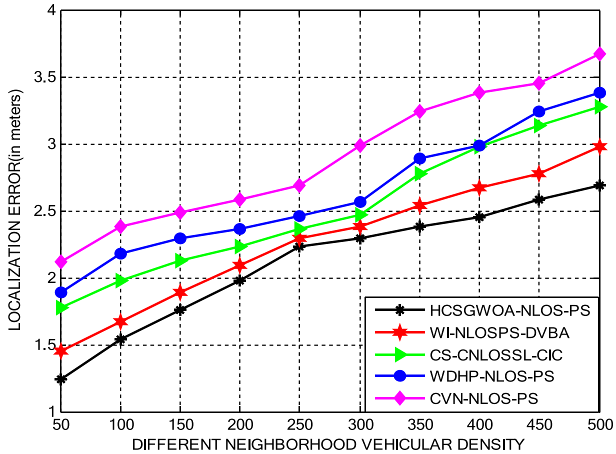

FIGURE 8 Localization Error of the Proposed HCSGWOA-NLOS-PS for Varying Vehicle Densities

HCSGWOA-NLOS-PS offers the best rate of localization and minimized localization error independent of the neighborhood vehicular densities in the network. This potential is mainly due to the incorporation of the position updating phenomenon of CSOA into GWOA that plays an anchor role in effective positioning of unknown NLOS nodes. The rate of localization of the proposed HCSGWOA-NLOS-PS with a corresponding increase in neighborhood vehicular densities is identified to be remarkable by 8.94%, 11.82%, 12.48% and 14.12% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis. The localization time incurred by the proposed HCSGWOA-NLOS-PS with a corresponding increase in neighborhood vehicular density is also proved to be excellent by 9.42%, 11.42%, 13.85% and 15.28% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis.

4.2 | Results of Simulation Experiments Conducted based on Varying Number of NLOS Nodes

In this section, the proposed HCSGWOA-NLOS-PS is compared with the benchmarked schemes based on delivery rate of warning message, rate of awareness, rate of localization and localization error for varying number of NLOS nodes in the vehicular network. This investigation is conducted with 500 vehicular nodes for a simulation time of 500 s and 40 reference nodes. Figures 9 and 10 present the delivery rate of warning messages and rate of awareness achieved by the proposed HCSGWOA-NLOS-PS and the benchmarked schemes for varying number of NLOS nodes in the network. The delivery rate of warning messages and rate of awareness achieved by the proposed HCSGWOA-NLOS-PS is estimated to be well maintained independent of the number of NLOS that hurdles the performance of the network in emergency situations. This predominant sustenance in the delivery rate of warning messages and rate of awareness with different degrees of NLOS nodes is mainly attained due to the utilization of NLCP that aids in positioning the

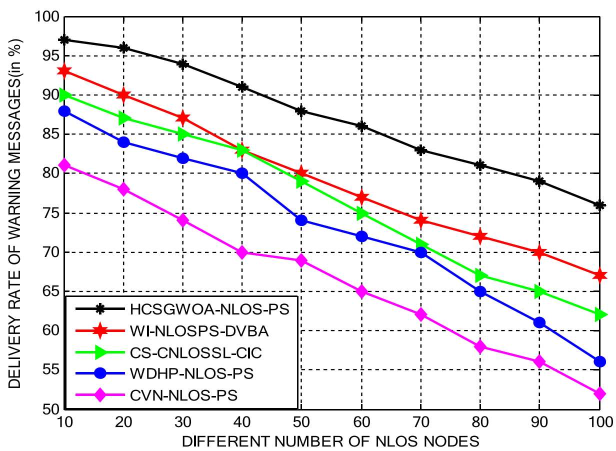

FIGURE 9 Delivery Rate of Warning Messages of the Proposed HCSGWOA-NLOS-PS for Varying Number of NLOS Nodes

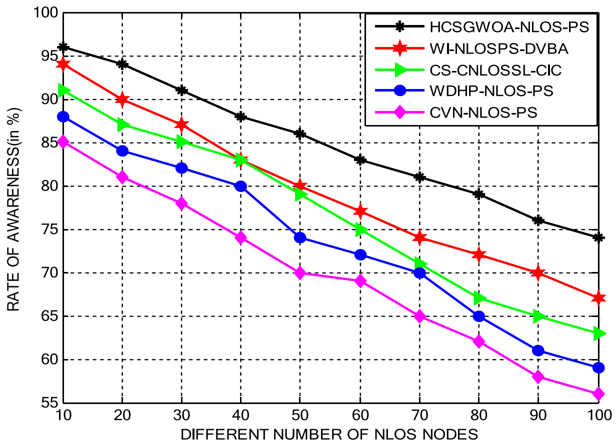

FIGURE 10 Rate of Awareness of the Proposed HCSGWOA-NLOS-PS for Varying Number of NLOS Nodes

unknown nodes with minimal effort by shrinking or expanding the rate of global and local optimization process. It is also capable of maintaining the tradeoff between global and local search abilities by preventing the localization error to the maximum extent. Thus, the delivery rate of warning messages achieved by the proposed HCSGWOA-NLOS-PS with a relative increase in NLOS nodes is identified to be remarkable by 8.42%, 9.79%, 12.84% and 14.12% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis. The rate of awareness facilitated by the proposed HCSGWOA-NLOS-PS with a relative increase in NLOS nodes is also determined to be excellent by 7.54, 9.42%, 10.98% and 12.46% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes considered for analysis.

Furthermore, Figures 11 and 12 portray the rate of localization and localization error attained by the proposed HCSGWOA-NLOS-PS and the benchmarked schemes for increasing number of NLOS nodes in the network. This

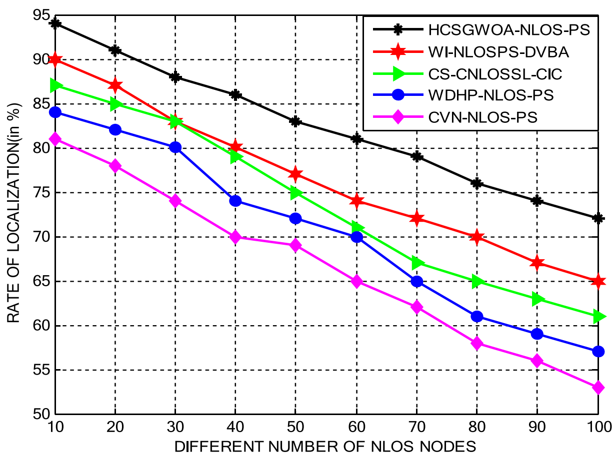

FIGURE 11 Rate of Localization of the Proposed HCSGWOA-NLOS-PS for Varying Number of NLOS Nodes

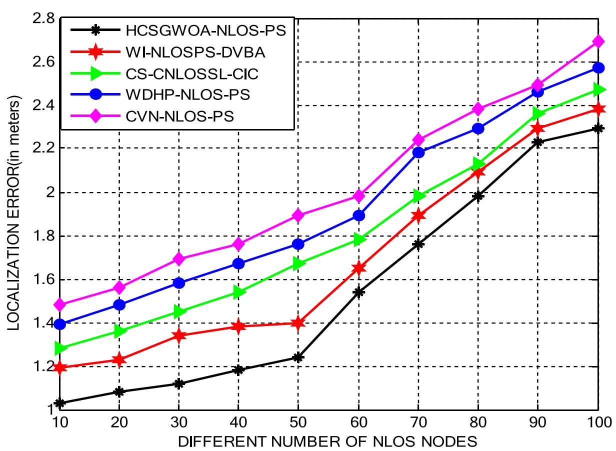

FIGURE 12 Localization Error of the Proposed HCSGWOA-NLOS-PS for Varying Number of NLOS Nodes

enhancement in the rate of localization with minimization in the localization time is made feasible by the proposed HCSGWOA-NLOS-PS due to its potentiality in widening and contracting the search space. This adaptive search space completely depends on the predicted distance between the unknown and the reference nodes based on 'AB_{Prob}' independent of the number of NLOS nodes in the network. It also includes a shrinking mechanism of CSOA that reduces the time incurred in positioning the NLOS nodes in the network. Thus, the rate of localization of the proposed HCSGWOA-NLOS-PS with a relative increase in NLOS nodes is identified to be remarkable by 9.14%, 11.21%, 13.18% and 15.42% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis. The localization time incurred by the proposed HCSGWOA-NLOS-PS with a relative increase in NLOS nodes is also determined to be excellent by 8.43%, 10.68%, 12.84% and 14.92% in contrast to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes considered for analysis.

4.3 | Results of Simulation Experiments Conducted based on Varying Number of Reference Nodes

In this section, the proposed HCSGWOA-NLOS-PS is compared with the benchmarked schemes based on the delivery rate of warning messages, rate of localization and localization time for varying number of reference nodes in the network. In this experimental investigation, the vehicular density (number of nodes is 500), the number of NLOS nodes (100 nodes) and simulation time are kept constant. Figures 13 and 14 highlight the predominance of the proposed HCSGWOA-NLOS-PS and its benchmarked schemes evaluated based on delivery rate of warning messages and rate of

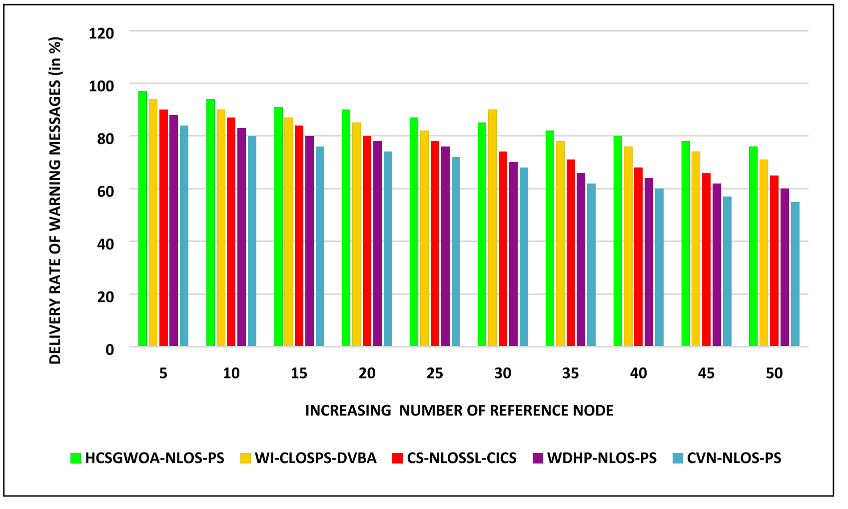

FIGURE 13 Delivery Rate of Warning Messages of the Proposed HCSGWOA-NLOS-PS for Varying Number of Reference Nodes

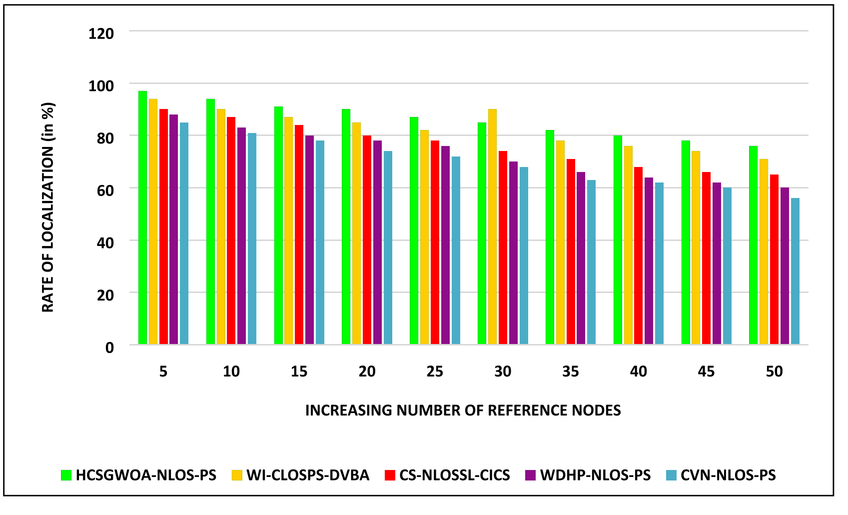

FIGURE 14 Rate of Awareness of the Proposed HCSGWOA-NLOS-PS for Varying Number of Reference Nodes

localization. The delivery rate of warning messages with a corresponding increase in reference nodes is identified to be sustained. This is mainly due to its accuracy in localizing the NLOS nodes which gets enhanced by including GWOA that prevents the limitation of the local search strategy inherent in CSOA. Similarly, the rate of localization with a relative increase in reference nodes is also estimated to be maintained by the usage of Flight Length (F_{Length}) and the probability of the awareness factor used in CSOA. The delivery rate of warning messages of the proposed HCSGWOA-NLOS-PS with increasing reference nodes is confirmed to be excellent by 5.72%, 6.94%, 7.38% and 8.94% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis. The rate of localization of the proposed HCSGWOA-NLOS-PS with increasing reference nodes is also proved to be excellent by 5.42%, 6.42%, 7.18% and 8.42% in contrast to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS, and CVN-NLOS-PS schemes taken for analysis.

Figure 15 depicts the localization time incurred by the proposed HCSGWOA-NLOS-PS for increasing number of reference nodes taken for NLOS node positioning. The localization time spent by the HCSGWOA-NLOS-PS for positioning NLOS nodes using reference nodes is significantly reduced by the inclusion of the modified update strategy of CSOA that relatively increases the probability of positioning the NLOS nodes with maximized accuracy. It also minimizes the localization time by incorporating a NLCP that decides the potential reference node used for positioning with reduced localization error. Thus, the localization time of the proposed HCSGWOA-NLOS-PS with a corresponding increase in the reference nodes is concluded to be considerably reduced by 6.72%, 7.85%, 8.94% and 10.21% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis.

4.4 | Results of Simulation Experiments Conducted based on Varying Elapsed Time

In this section, the proposed HCSGWOA-NLOS-PS is compared with the benchmarked schemes based on rate of awareness, end-to-end delay and channel utilization for different elapsed times of simulation. In this experimental investigation, the vehicular density (number of nodes is 500), the number of NLOS nodes (100 nodes) and reference nodes are kept constant (20 nodes).

Figures 16 and 17 demonstrate the rate of awareness and end-to-end delay of the proposed HCSGWOA-NLOS-PS with increasing elapsed time. The proposed HCSGWOA-NLOS-PS is determined to be capable of facilitating enhanced and sustainable rate of awareness with reduced end-to-end delay on par with the baseline approaches considered for analysis. This predominant potency of the proposed HCSGWOA-NLOS-PS with increasing elapsed time is mainly due to three important reasons. Firstly, it uses the strategy of adaptive balancing mechanisms that provides more weight to reference nodes that are in proximity and less weight to reference nodes that are afar off relative to the position of the unknown NLOS nodes. Secondly, it uses the universality accepted exploration capability of CSOA that enhances the global positioning ability of NLOS nodes through reference nodes. Finally, it also includes the merits of memory updating phenomenon of CSOA into GWOA for effective positioning. Thus, the rate of awareness of the proposed HCSGWOA-NLOS-PS with increasing time is determined to be superior by 3.96%, 4.78%, 6.16% and 7.38% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis. Likewise, the end-to-end delay of the proposed HCSGWOA-NLOS-PS for increasing time is determined to

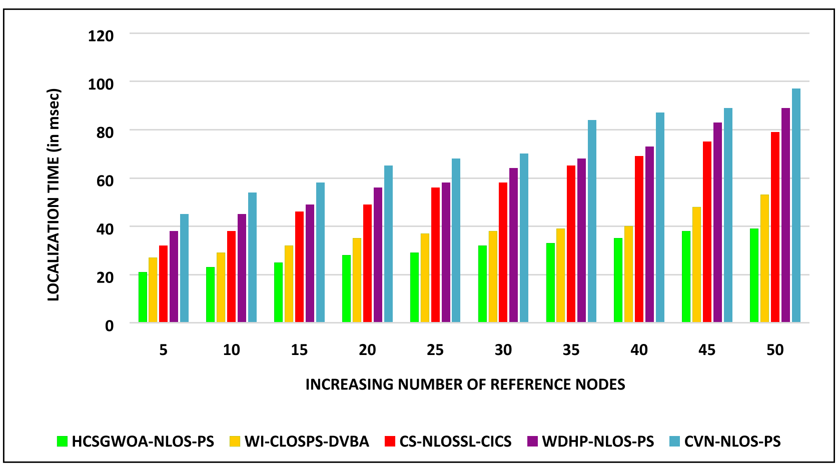

FIGURE 15 Localization Time of the Proposed HCSGWOA-NLOS-PS for Varying Number of Reference Nodes

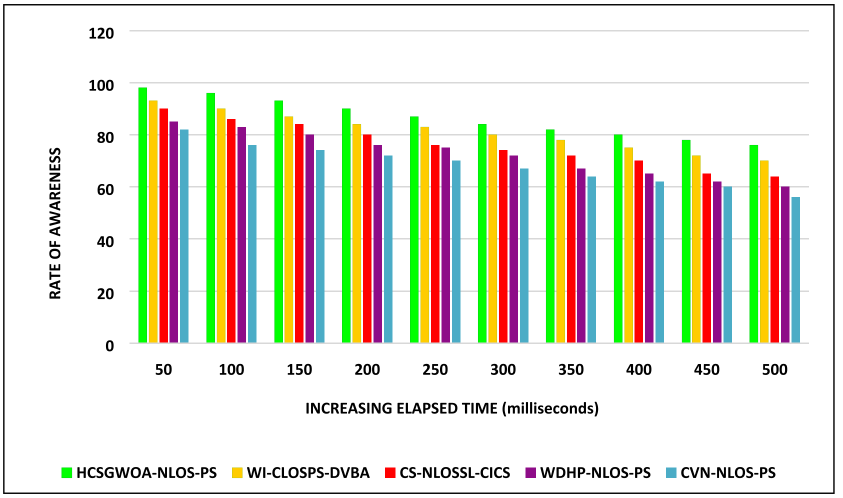

FIGURE 16 Delivery Rate of Warning Messages of the Proposed HCSGWOA-NLOS-PS for Increasing Elapsed Time

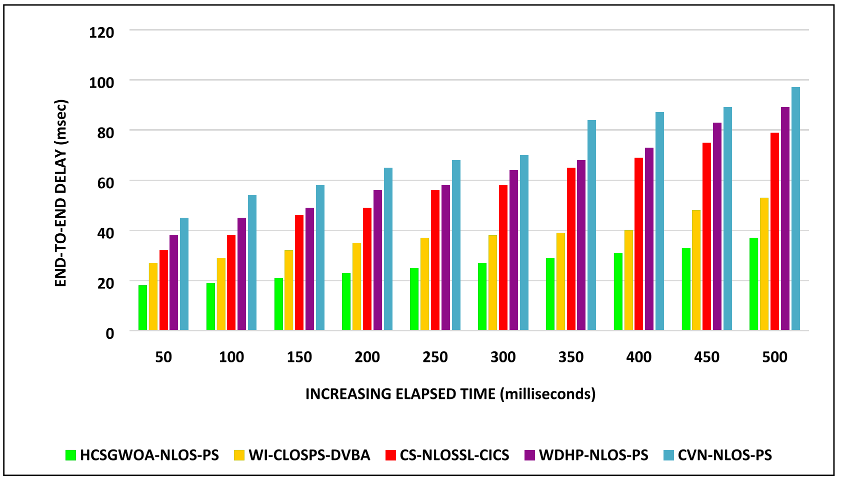

FIGURE 17 End-to-end Delay of the Proposed HCSGWOA-NLOS-PS for Increasing Elapsed Time

be excellent by 4.58%, 5.68%, 6.84% and 7.94% in contrast to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes considered for analysis.

Figure 18 presents the channel utilization of the proposed HCSGWOA-NLOS-PS for increasing elapsed time. The proposed HCSGWOA-NLOS-PS is determined to be significant in terms of channel utilization, since it is capable of changing the rate of exploitation and exploration involved in positioning the NLOS nodes with utmost accuracy even

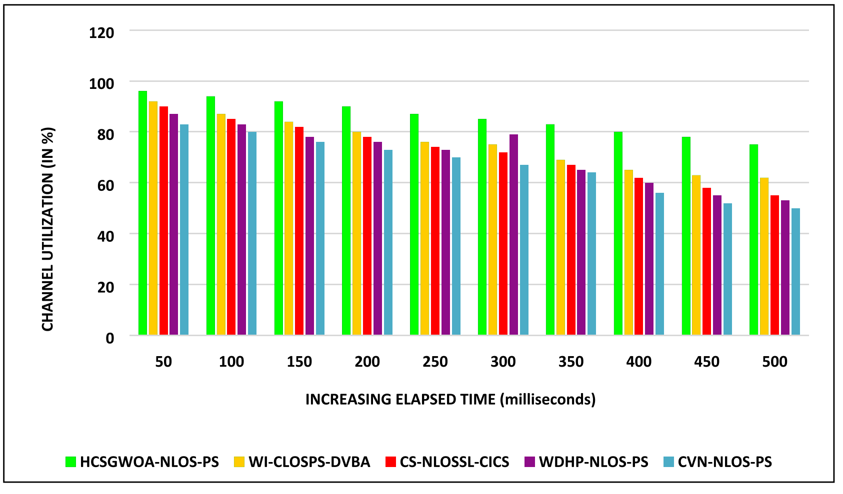

FIGURE 18 Channel Utilization of the Proposed HCSGWOA-NLOS-PS for Increasing Elapsed Time

with the increase in elapsed time. The capability of the proposed scheme aids in the ideal usage of the channel during emergency message propagation and delivery for preventing channel contention and broadcast storm situations. The channel utilization of the proposed HCSGWOA-NLOS-PS with increasing elapse time is determined to be superior by 3.12%, 4.65%, 5.8% and 6.18% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis.

Table 3 presents the comparative results of the proposed scheme with the existing works presented in the related work section.

In addition, the HCSGWOA-NLOS-PS and the compared WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS, and CVN-NLOS-PS schemes are evaluated based on mean, Standard Deviation (SD), and Root Mean Square Error (RMSE) with different NLOS scenarios. Tables 4 and 5 present the mean and SD of the proposed HCSGWOA-NLOS-PS and the compared WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes with respect to bad urban, urban, suburban and rural environment of NLOS scenarios. The mean and SD of the proposed HCSGWOA-NLOS-PS are also determined to be stable when compared to the baseline WI-CLOSPS-DVBA, CS-NLOSSL-CIC,

TABLE 3 Comparison Results of the Proposed Scheme with the Reviewed Works

Authors	Decrease in contention rate	Decrease in energy consumption	Decrease in vehicle collision rate	Increase in obstacle identification rate
Proposed HCSGWOA-NLOS-PS	32.28%	28.56%	29.21%	34.48%
Abumansoor and Boukerche[18]	21.38%	21.68%	21.29%	26.54%
Soleymani et al.[19]	23.64%	16.72%	16.84%	15.94%
Zubairu[20]	20.19%	14.84%	17.21%	16.24%
Alodadi et al.[21]	18.42%	18.29%	18.48%	19.52%
Amuthan and Kaviarasan[22]	25.38%	17.48%	16.98%	21.32%
Amuthan and Kaviarasan[23]	16.21%	17.46%	18.96%	20.94%
Lassoued and Bonnifait[24]	17.32%	19.32%	22.38%	22.98%
Amuthan and Kaviarasan[25]	18.56%	19.34%	19.42%	22.12%
Abdelatif et al.[26]	19.42%	21.32%	19.46%	18.32%
Soleymani et al.[27]	18.94%	20.45%	14.38%	18.94%
Sivasubramanian and Subramaniam[28]	17.26%	23.38%	21.84%	13.48%
Kim[29]	10.84%	20.93%	20.32%	15.69%

TABLE 4 Mean Error Estimate of the Proposed HCSGWOA-NLOS-PS for Different NLOS Scenarios

	Mean error estimate for different NLOS scenarios							
	Number of NLOS Nodes-5				Number of NLOS Nodes-10			
Compared mechanisms	Bad urban	Urban	Suburban	Rural	Bad urban	Urban	Suburban	Rural
HCSGWOA-NLOS-PS	0.0244	0.0226	0.0224	0.0246	0.0263	0.0273	0.0274	0.0266
WI-CLOSPS-DVBA	0.0325	0.0302	0.0352	0.0373	0.0348	0.0368	0.0372	0.0382
CS-NLOSSL-CIC	0.0364	0.0409	0.0454	0.0434	0.0398	0.0388	0.0399	0.4121
WDHP-NLOS-PS	0.0385	0.0347	0.0323	0.0382	0.0421	0.0432	0.0456	0.4562
CVN-NLOS-PS	0.0397	0.0331	0.0472	0.0421	0.0426	0.0432	0.0438	0.4653

TABLE 5 Standard Deviation of the Proposed HCSGWOA-NLOS-PS for Different NLOS Scenarios

Compared mechanisms	Mean estimated for different NLOS scenarios							
	Number of NLOS Nodes-5				Number of NLOS Nodes-10			
	Bad urban	Urban	Suburban	Rural	Bad urban	Urban	Suburban	Rural
HCSGWOA-NLOS-PS	0.0412	0.0410	0.0411	0.0409	0.0512	0.0513	0.0514	0.0910
WI-CLOSPS-DVBA	0.0564	0.0568	0.0578	0.0534	0.0868	0.0864	0.0865	0.866
CS-NLOSSL-CIC	0.0568	0.0569	0.0576	0.0584	0.0672	0.0672	0.0683	0.0695
WDHP-NLOS-PS	0.0578	0.0578	0.0589	0.0593	0.0688	0.0688	0.0721	0.0732
CVN-NLOS-PS	0.0687	0.0687	0.0594	0.0598	0.0694	0.0694	0.0731	0.0738

TABLE 6 RMSE of the Proposed HCSGWOA-NLOS-PS for Different NLOS Scenarios

Compared mechanisms	Mean estimated for different NLOS scenarios							
	Number of NLOS Nodes-5				Number of NLOS Nodes-10			
	Bad urban	Urban	Suburban	Rural	Bad urban	Urban	Suburban	Rural
HCSGWOA-NLOS-PS	0.0764	0.0766	0.0765	0.0762	0.0862	0.0864	0.0862	0.0861
WI-CLOSPS-DVBA	0.0897	0.0921	0.0923	0.0932	0.0935	0.0948	0.0954	0.0959
CS-NLOSSL-CIC	0.0895	0.0934	0.0945	0.0956	0.0959	0.0966	0.0967	0.0969
WDHP-NLOS-PS	0.0824	0.0986	0.0989	0.0824	0.0924	0.0946	0.0952	0.0943
CVN-NLOS-PS	0.0923	0.0929	0.0929	0.0938	0.0938	0.0968	0.0965	0.0956

WDHP-NLOS-PS and CVN-NLOS-PS schemes, since accuracy involved in positioning is adapted depending on the number of NLOS nodes and the distance between the reference node and the unknown NLOS vehicles in the network.

Table 6 presents the RMSE of the proposed HCSGWOA-NLOS-PS and the compared WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes with respect to bad urban, urban, suburban and rural environment of NLOS scenarios. The RMSE of the proposed HCSGWOA-NLOS-PS is also determined to be stablewhen compared to the baseline WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes, since the error involved in NLOS positioning is handled independent of vehicle density in the network.

5 | CONCLUSION

The proposed Hybrid Crow Search and Grey Wolf Optimization Algorithm-based NLOS Positioning Scheme (HCSGWOA-NLOS-PS) is a reliable NLOS positioning algorithm that derives the exploitation capability of GWOA and exploration potential of CSOA in order to facilitate accurate localization. It includes the merits of the enhanced weight-based clustering algorithm for pointing regions and includes fourfold cross validation in the process of prediction. It incorporates three vital parameters such as an adaptive balance strategy, modified position updating mechanism and NLCP associated with GWOA and CSOA for mutual and predominant utilization in the effective and efficient NLOS localization process. It is proposed for enhancing the delivery rate of warning messages, rate of awareness and channel utilization during emergency situations. The simulation experiments of the proposed HCSGWOA-NLOS-PS conducted using the EstiNet 8.1 Simulator clearly demonstrates its predominance in the scenario of suburban and urban areas. The mean delivery rate of warning messages and rate of awareness achieved by the proposed HCSGWOA-NLOS-PS for varying neighborhood vehicular densities is identified to be remarkable by 11.29% and 10.84% when compared to the benchmarked WI-CLOSPS-DVBA, CS-NLOSSL-CIC, WDHP-NLOS-PS and CVN-NLOS-PS schemes taken for analysis. Similarly, the proposed HCSGWOA-NLOS-PS enhances the rate of localization on an average by 12.27% with mean localization time minimization rate of 11.32% in contrast to the benchmarked schemes considered for analysis. Further, the delivery rate of warning messages and rate of awareness introduced by the proposed HCSGWOA-NLOS-PS for increasing reference nodes also proves to be excellent by 7.14% and 6.24% when compared to the baseline schemes taken for investigation. In the near future, it is also planned to formulate and implement a hybridized GWOA and Whale Optimization Algorithm (WOA) for NLOS node positioning in order to compare and determine the superior level of these techniques. The hybridized CSOA and GWOA can be utilized in the process of sensor node localization, Cluster Head (CH) selection in sensor networks, task scheduling in a cloud computing environment, and implementing clustering protocol in Flying Ad hoc NETworks (FANETs).

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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