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ORIGINAL RESEARCH

Weighted inertia-based dynamic virtual bat algorithm to detect NLOS nodes for reliable data dissemination in VANETs

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Abstract

Vehicular ad hoc network (VANET) is the significant network suitable for the deployment of risk-free environment that ensures least congestion and secure collaboration among the vehicular nodes of the network. The maintenance of connectivity among vehicular nodes is influenced by non line of sight (NLOS) nodes by introducing broadcasting storm and channel congestion during data dissemination. The problem of the NLOS node localization is considered as the optimization process for reducing the latency incurred in emergency information distribution. In this paper, a weighted inertia-based dynamic virtual bat algorithm (WIDVBA) is proposed for enhancing the characteristics of the traditional Virtual bat scheme that integrates the merits of simulated annealing (SA) and particle swarm optimization (PSO) for effective NLOS node localization. This proposed WIDVBA prevents the problem of premature convergence by incorporating the benefit of a weighted inertial factor compared to the traditional dynamic virtual binary bat-based NLOS localization approaches. This proposed WIDVBA dynamically increase and decrease the area of exploration and degree of exploration depending on the location of the NLOS nodes. The performance of WIDVBA studied using EstiNet 8.1 reveals that the number of NLOS nodes and time incurred in detecting NLOS nodes potentially increases with an increase in the neighbor awareness rate on par with the compared NLOS detection techniques.

Keywords Non line of sight (NLOS) nodes · Weighted Inertia-based dynamic virtual bat algorithm · Intensity parameter · Global search rate · Virtual bats

1 Introduction

In general, the vehicle drivers in VANET seem to exhibit a delayed course of reaction to an emergency situation or alarm for which rapid action is essential (Gazzah et al. 2015). This delayed reaction from the drivers increase the probability of collision among emergency and non-emergency vehicles that leads to huge loss of life or damage to the physical road infrastructures (Yousefi et al. 2014). Inaccurate perception and inadequate information updates about an emergency situation or event is identified as the prime cause for drivers' delayed response as they fail to guide them in decision making under critical contexts.Precise information and cognition of emergency events is responsible for guiding the vehicles on the road and ensuring optimal decisions that guides each movement of the vehicles under emergency scenario (Li et al. 2016). It is also responsible for preventing wrong conclusions that result in collisions and fatal accidents. These collisions and accidents delaythe arrival of police patrol vehicles or ambulances during recovery. The probability of collision among vehicles during emergency is maximum as the time required by the emergency vehicles to reach the destination is limited (Teng et al. 2012). The probability of accidents created by emergency vehicles is identified to be nearly 25% greater than the accidents induced by the non-emergency vehicles on the road. It is confirmed that the number of accidents made by the non-emergency vehicles and emergency vehicles always happen at the road intersections as the visibility or coverage of the vehicular nodes are proved to be reduced at this point (Li et al. 2013).

Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I)-based data transfer among vehicles in VANET is made feasible only based on the deployment of intelligent

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transportation systems (ITS). This ITS enabled V2V and V2I is primarily responsible for sharing and updating position, velocity and frequency of the emergency or non-emergency vehicles in shorter span of time (Zhang et al. 2014). These precise information related to vehicles is necessary to guide the vehicle drivers for rapid and reactive actions that eliminates the possibility of collisions between vehicles travelling on the road (Fujita and Ohtsuki 2008). Further, the time in data dissemination is influenced by objects like tall vehicles, foliage's, buildings or factors like vehicle density. Similarly, intentional or non-intentional behavior of non line of sight (NLOS) nodes also contribute to huge delay as the vehicles on the road are of varying shapes, composition, speeds and densities (Sorrentinoet al. 2012). NLOS nodes are mainly responsible for increased delay since they prevent the number of messages initiated by the source vehicle from reaching the destination vehicle. This failure in updating information induced by the NLOS nodes end up with fatal accidents or serious accidents (Zhanget al. 2012a, b, c). Hence, the NLOS nodes need to be localized at a rapid and precise rate such that the goal of minimizing delay is met. In addition, a comprehensive protocol, which is capable of minimizing the latency time in delivering emergency messages becomes essential in VANET (Gentner and Groh 2011). Hence, the primary issue that is needed to be sustained in VANET communication is the establishment and maintenance of maximum coverage between the vehicles of the network such that the time delay between the emergence and reception of emergency message is optimally reduced. The meta-heuristic algorithms are determined to be effective in localizing NLOS nodes in the vehicular networks. One of the potential algorithm that formed the basis behind the formulation of the proposed WIDVBA scheme is the dynamic inertia weight binary bat algorithm with neighborhood search (Huang et al. 2017). This dynamic inertia weight binary bat algorithm is a binary version of the traditional bat algorithm, which is proved to highly competitive than the existing binary versions of heuristic algorithms in the literature. This dynamic inertia weight binary bat algorithm was proposed for resolving the issue of premature convergence, which is considered as the primitive limitation of the binary bat algorithm. This dynamic inertia weight binary bat algorithm also possesses inertial weight parameter that aids them in facilitating the prevention of the tradeoff between the rate of exploitation and exploration in NLOS node identification. Motivated by the behavior of this dynamic inertia weight binary bat algorithm, the idea of formulating the proposed WIDVBA approach for effective localization of NLOS nodes is initiated.

In this paper, WIDVBA is contributed as an enhanced dynamic bat-based swarm intelligent localization algorithm which is phenomenally improvised using the concept of inertial weight. This incorporation of inertial priority helps the bat algorithm to localize NLOS nodes at a rapid rate such that the delay in emergency data transmission is predominantly reduced. The dynamic update rules related to the velocity, frequency and position of vehicular movement in the search space help WIDVBA to establish and maintain maximum coverage between the vehicles of the network. The potential of WIDVBA is investigated using the EstiNet simulation tool for quantifying its superiority over the benchmarked NLOS node localization schemes. Performance metrics like neighborhood awareness rate, execution time, the time incurred in localization, the channel utilization rate is used for comparative investigation of WIDVBA since they are proved as the significant parameters that are highly impacted during the existence of NLOS nodes in the vehicular network (Zhang et al. 2012a, b, c).

In addition, the major contributions of the proposed WIDVBA scheme are listed as follows.

1. The proposed WIDVBA scheme facilitates significant detection of NLOS nodes by preventing the search solution from falling into a local optimal point.
2. The utilization of a weight inertial factor in the proposed WIDVBA scheme aided in monitoring the search solution by flexibly adjusting its value based on the feedback parameters shared between the vehicular nodes.
3. The incorporation of self learning factor with weight inertial factor in the proposed WIDVBA scheme also increases the search efficiency that focuses on rapid NLOS localization.

The forthcoming sections of the paper are structured as follows. Section 2 presents a potential literature review on some of the existing works proposed by the novel researchers towards the objective of localizing NLOS nodes. Section 3 enumerates a detailed step by step algorithmic activity of WIDVBA algorithm contributed for optimal localization of NLOS nodes. The details related to the simulation-based experimental conduction and investigation of WIDVBA's result analyses are portrayed in Sect. 4. Section 5 concludes the paper by summarizing major contributions of the proposed WIDVBA with future possibilities of improvement.

2 Related work

A number of potential works focusing on effective localization of NLOS nodes in the vehicular network were contributed in the literature from the past decade. But only a considerable number of potential works were proposed for concentrating on the delay reduction issue which is necessary during emergency data delivery. The most significant among those research works are comprehensively reviewed and detailed below for identifying their merits and limitations.

Initially, an intentional and malicious category of NLOS nodes under Sybil attack was localized by (Xiao et al. 2006) using signal strength. In this localization mechanism, signal strength is periodically updated between the collaborating nodes of the network. This updating of signal strength is mainly to spot out an effective neighborhood vehicular nodeunder NLOS scenario. This localization scheme is also a distributed approach in which each node is capable of measuring its own signal strength and share it among other interacting vehicular nodes of the network for justifying their precise position. The computation and communication overhead incurred in the deployment of this algorithm in the network is proving to be high as the measurement of signal strength itself leads to huge energy consumptions and packet re-transmissions. A trust model for detecting NLOS nodes was proposed (Leinmüller et al. 2008) for estimating and valuating the trustworthiness of the neighboring vehicles during emergency message transfer. The trust factor of the vehicular nodes is estimated through multi-capability sensors for quantifying their reliability towards emergency message transfer. This multi-capability sensor-based NLOS detection approach also incurs large amount of energy consumptions and packet re-transmissions during sensing process.

Then, a GRANT protocol-based localization mechanism (GRANTBLM) was contributed (Capkun et al. 2008) for preventing huge processing at the destination during emergency message reception. ThisGRANT protocol-based NLOS detection approach uses a specially designated base station referred as covert node for localization. This GRANT protocol inspired scheme is also phenomenal, even when the received signal strength index is minimized. The utilization of covert node is potentenough in preventing the exact location of the node from being known by the malicious intruders of the network. The main drawback of this covert node scheme is its passive nature that necessarily requires the generation of secret key without checking the necessity of the generation. An echo-packet-based NLOS localization scheme was proposed Sastry et al. (2003) for resolving the influence of NLOS nodes. This echo packet-based localization approach is developed as the challenge response scheme for accurate detection of NLOS nodes. This echo-packet-based detection scheme for the first time used a secure in-region search domain for localization and it was the premier mechanism that incurred minimum hardware for implementation. It also used ultrasonic and real time invariant fight scheme for verifying the position of the nodein the intersections of road. This scheme suffers from increased delay when the number of NLOS nodes increases over the threshold which is computed based on the number of vehicular nodes of the network.

Furthermore, a co-operative volunteer election-based localization mechanism (CVEBLM) was proposed Alodadiet al. (2017) for context sensitive components that provide the support of embedding on-board units. These on-board units in CVEBLM are responsible for collecting, investigating and decision making during the exchange of information in emergency scenarios. CVEBLM is proved to be superior compared to GRANTBLM and echo packet-based localization scheme as they employ the process of electing a node among the collaborating nodes as the volunteer for effective localization of obstacles during data delivery. CVEBLM is also proved to be better in ensuring reduced response time, decreased communication overhead and improved channel utilization rate due their rapid process of detecting NLOS nodes. The only drawback of CVEBLM is the time incurred in the process of electing volunteer nodes, which is assumed to be relied without estimating its genuineness. A time of flight-based co-operative mechanism was proposed (Song et al. 2008) for preventing duplicate and false notifications received from the nodes during localization. This co-operative mechanism uses Time of Flight as the metric for evaluating the distance of the vehicular node from the reference nodes based on which effective localization need to be performed. Then foci-based elliptical computation is performed in assisting the reference nodes inaccurate localization of NLOS nodes. The main shortcoming of this Time of Flight-based co-operative mechanism lies in the computation overhead, which increases with an increase in vehicular nodes of the network. Position verification secure message-based localization mechanism (PVSMBLM) (Abumansoor and Boukerche 2012) was proposed for securing the identification of vehicles based on hash indexing scheme. This hash index-based PVSMBLM is effective enough in localizing NLOS nodes compared to the time of flight and echo packet oriented detection methodologies. The use of hash-based secret key improves the efficiency in detecting NLOS nodes as they are unique in localizing the vehicular nodes which are in the reach out area. The core limitation of this approach is the need of generating secret key in each and every session and this generation increases the communication overhead in the network. In addition, a hybrid localization scheme inspired by the benefits of Pedestrian Dead Reckoning for investigating the factor of Received Signal Strength was proposed in order to handle NLOS situations (Ciabattoniet al. 2017). This hybrid localization scheme was contributed to prevent the issues that emerge under NLOS situations through the estimation of step length, heading estimation and beacon information integration. This hybrid localization scheme was also confirmed to enhance the neighborhood awareness, which in turn enhances the degree of data dissemination rate.

The aforementioned limitations of the reviewed research works formed the base for the formulation of Weighted

Inertia-based dynamic virtual bat algorithm (WIDVBA) which is formulated for minimizing delay and improving precision in localization of NLOS nodes.

3 Weighted inertia-based dynamic virtual bat algorithm (WIDVBA) for NLOS node detection

The proposed Weighted Inertia-based dynamic virtual bat algorithm (WIDVBA) inspires the behavior of real bats by using the phenomenal advantages of simulated annealing (SA) and particle swarm optimization (PSO). WIDVBA is an effective NLOS node localization algorithm that reduces the area of exploration and degree of exploration when the location of the NLOS nodes under emergency is shorter and increases the region of exploration and exploitation when their distance decreases. The traditional SA and PSO are integrated because the updating of vehicles' location and velocity are vitally analyzed and updated at each point in data dissemination. The search agents (referred as virtual bats) needed for detecting NLOS nodes are implemented in each and every vehicular node independent to their context of emergency and non-emergency. The number of search agents used for detecting NLOS nodes varies from 2 to a maximum of $\frac{n}{2}$ where 'n' is the number of nodes in the vehicular network. These search agents are initiated from any arbitrary nodes of the network with position 'P_i' and rate of search scope as '$R_{SS(i)}$'. During the exploration phase, the rate of search scope dynamically varies depending on the distance of the search agent and NLOS nodes. i.e., the rate of search scope increases with increase between the distance of the search agent and NLOS nodes and in contrast, the rate of search scope decreases when the distance of the search agent and NLOS node decreases. In WIDVBA, three vectors corresponding to position, frequency and velocity are initialized and updated periodically at each stepwise time 't' based on Eqs. (1), (2) and (3).

$$P_i(t+1) = P_i(t) + V_{P(i)}(t+1), \tag{1}$$

$$F_{r(i)} = F_{r(low)} + \left(\left(F_{r(high)} - F_{r(low)}\right) * \alpha_{(0,1)}\right), \tag{2}$$

$$V_{P(i)}(t+1) = V_{P(i)}(t+1) + \left(P_{i(t)} - BP_{i(t)}\right)F_{r(i)}, \tag{3}$$

where $\alpha_{(0,1)}$ is the uniformly distributed random vector which varies between 0 and 1. The aforementioned equations clearly portray that change in frequencies of WIDVBA algorithm ensures better optimal solution in detecting NLOS nodes during emergency message transfer for response and decision making. These equations also promote maximum exploration potential and they also try to ensure exploitation potential to certain degree. The degree of exploration and exploitation in detecting NLOS nodes during emergency message transfer is achieved using random walk for guaranteeing much intensification based on Eq. (4).

$$P_{i(new)} = P_{i(old)} + \beta_{[-1,1]} * \vec{M}_{s(t)}, \tag{4}$$

where $P_{i(old)}$is a randomly chosen position among all feasible positions of the vehicular nodes under NLOS scenario which is used for appropriately used for determining the exact position of the NLOS nodes under interaction. This exact determination of NLOS nodes is achieved using β and $\underset{s(t)}{\vec{M}}$ that relates to the randomly chosen integer that varies from -1 to 1 and mean distance from the reference nodes (anchor nodes) to the NLOS nodes. In this context, global and local search for estimating the exact location of NLOS nodes can be facilitated by the algorithm. This WIDVBA further uses control parameters such as intensity parameter $I_{p(i)}$ and Global search rate $R_{GS(i)}$ that are updated based on Eqs. (5) and (6).

$$M_{S(i)}(t+1) = \delta M_{S(i)}(t), \tag{5}$$

$$R_{GS(i)}(t+1) = R_{GS(0)}\left(1 - e^{-\kappa t}\right), \tag{6}$$

where δ and κ is similar to the factor of cooling used in SA (Yılmaz and Küçüksille 2015) and it varies between 0 and 1. The value of $M_{S(i)}(t)$ is used for decreasing or increasing the rate of exploration and exploitation for detecting accurate position of NLOS nodes and further, intensity parameter $I_{p(i)}$ and global search rate $R_{GS(i)}$ are updated periodically for improving the accurate estimation of NLOS nodes.

As mentioned earlier, the detection of position and velocity related to vehicular nodes analogies the process of updating position and velocity of vehicles using method of particle swarm optimization (Cai et al. 2016). When Eq. (1) is investigated, it is clear that it comprises of two parts in which first part corresponds to the velocity updating of vehicles $V_{p(i)}(t)$ and the second part $\left(P_{i(t)} - BP_{i(t)}\right)F_{r(i)}$ aids in controlling the position during the movement of the vehicles using best determined position of vehicles $BP_{(i)}(t)$ under NLOS scenario. The first and second parts of Eq. (1) are also responsible for achieving local and global search for NLOS node detection. But, the first part of Eq. (1) drastically minimizes the rate of convergence and the second part of Eq. (1) fails in mature convergence. It is also inferred that the use of neigbhourhood bat (reference nodes called anchor nodes) are excellent in accurate identification of NLOS nodes during emergency message dissemination (Shi and Eberhart 2009). In this improved WIDVBA algorithm, update equation of vehicular nodes' velocity of Eq. (1) is modified into Eq. (7) based on information gained from the reference nodes of the network.

$$V_{P(i)}(t+1) = I_{WF} * V_{P(i)}(t+1) + \left(\left(P_{i(t)} - BP_{i(t)}\right) * F_{r(i)} * \rho_1\right) + \left(\left(P_{i(t)} - P_{k(t)}\right) * F_{r(i)} * \rho_2\right). \tag{7}$$

Under $\rho_1 + \rho_2 = 1$.

In this context, I_{WF} is the parameter of inertial weight derived using Eq. (9) for balancing the global and local intensification during the search process that converges the solution 'i' by the process of sustaining the old velocity under consideration. $V_{P(i)}(t)$ and $P_{k(t)}$ refers to the optimal solution randomly chosen from the feasible position and velocity updates which satisfies the condition $i \neq k$ with ρ_1 as dynamic and self-learning factors of the best optimal solution $\left(0 \leq \rho_2 \leq 1\right)$ computed using Eq. (8) and ρ_2 as dynamic and learning parameter of 'kth' feasible solution $\left(1 \leq \rho_2 \leq 0\right)$ based on the condition $\rho_1 + \rho_2 = 1$

$$\rho_1 = 1 + \left(\rho_{init} - 1\right)\left(\frac{i_{\max} - i}{i_{\max}}\right)^n, \tag{8}$$

where ρ_{init} is the initial dynamic and self-learning factor that guides to determine the position of the NLOS nodes rather than trapping into an local optimum point of searching, $i$and $i_{\max}$ denotes the current and maximum iterations used for accurate estimation of NLOS nodes' position with 'n' as the modulation index of non-linear property. As aforementioned, increase in ρ_1 non-linearly increases its value from ρ_{init} to 1 and similarly the value of $\rho_2$decreases from $\left(1 - \rho_{init}\right)$ to 0 respectively. Further, larger value of ρ_1 and smaller value of ρ_2 enables the search agents to converge the space of searching the position of NLOS nodes and in contrary, smaller value of ρ_1 and larger value of ρ_2 enables the search agents to diverge the space of searching. Thus WIDVBA algorithm is effective enough in controlling the search space such that the position of the NLOS nodes can be determined by alternating the process of exploration to exploitation. In WIDVBA algorithm, the value of ρ_1 and ρ_2 are determined by utilizing the value of 0.5 and 3 respectively.

Furthermore, the method of dynamic inertial weight approach is used in WIDVBA algorithm for controlling the magnitude for velocity using Eq. (9) which is dynamically alternated for estimating the accurate position of the NLOS nodes

$$I_{WF} = I_{WF(Max)} * \exp\left(-A_{IR} * \frac{i}{i_{\max}}\right)^{A_{IR}}, \tag{9}$$

where $A_{IR}$is the exploration constant greater than 1 (set to 1.5) with maximum inertial weight of $I_{_{WF(Max)}}$ (set to 0.6) for ensuring exploration and exploitation in a large scale based on Lei and Pu (2014).

Once WIDVBA algorithm determines the position of NLOS nodes which is changed after each 'r' iterations then the exploitation constant for search is derived using Eq. (10)

$$A_{IR(new)} = \rho_1 * \rho_2 * A_{IR} \text{ when } BP_{i(t)}^{(i+r)} < BP_{i(t)}^{(i)}, \tag{10}$$

and in contrast, if the position of NLOS nodes is not changed even after each 'r' iterations then the exploitation constant for search is derived using Eq. (11)

$$A_{IR} = A_{IR} \text{ when } BP_{i(t)}^{(i+r)} \geq BP_{i(t)}^{(i)}, \tag{11}$$

where $BP_{i(t)}^{(i+r)}$ and $BP_{i(t)}^{(i)}$ is the initial and the updated position of the NLOS node after 'r' iterations.

Finally, the updated position of the NLOS nodes is determined using Eq. (12) based on updated equation of velocity defined in Eq. (7)

$$P_{i(NEW)}(t+1) = P_{i(OLD)}(t) + V_{P(i)}(t+1). \tag{12}$$

This position of NLOS node is the two dimensional coordinate of 'x' and 'y' for precisely locating its presence in the two-dimensional defined topological search space.

4 Simulation results and Investigation

The significance of WIDVBA is explored and compared with the potential of PVSMBLM, CVEBLM and GRANTBLM through EstiNet network simulator. EstiNet network is used for the implementation and comparison of WIDVBA with PVSMBLM, CVEBLM and GRANTBLM techniques since they enable potent capabilities like the current IEEE 802.11p/1609 VANET network simulation and real destination-based vehicular movement that are possible on the road lanes of VANET. The assumptions and modifications enabled in the simulator for the implementation of WIDVBA are (1) routing information table is created in OBU of vehicular nodes for constant detection of unreachable nodes like NLOS nodes, (2) the data related to routing information table of each vehicular nodes are considered to be shared with all the neighbouring vehicular nodes that are possible in a time domain, (3) the data pertaining to the routing information table associated with each vehicular node is considered to be periodically updated for every 2 s and (4) the routing information table of each vehicular nodes is assumed to possess distance of each vehicle from the road intersections, directions, lane position of neighbouring vehicles with vehicle ID. In addition, the simulation parameters and its associated value used for the deployment of WIDVBA is listed in Table 1.

Table 1 Simulation parameters and values-WIDVBA

Parameters used for simulation	Values
Area of simulation	1500 m × 15000 m
Time of simulation	350 s
Range of transmission	200 m
Mobility generator type	OpenStreetMap
Maximum Vehicles' speed	50 m/h and 70 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	250

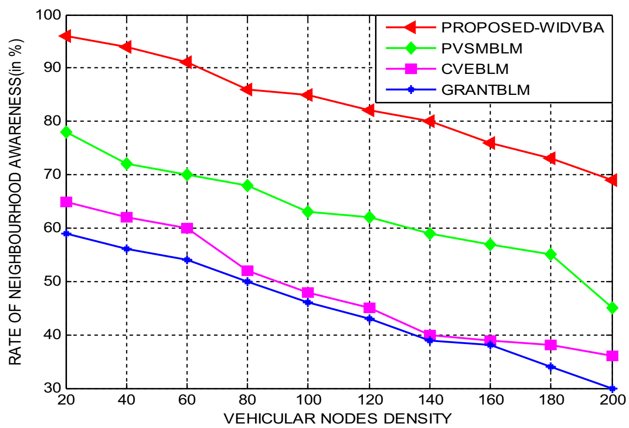

Fig. 1 WIDVBA-rate of neighbourhood awareness-vehicular node density

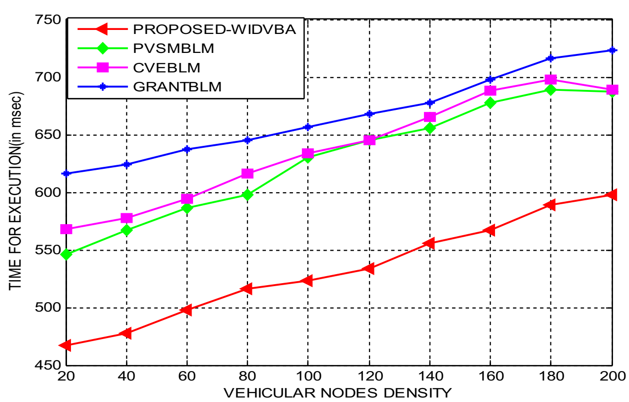

Fig. 2 WIDVBA-time of execution—vehicular node density

Initially, the simulation experiments of WIDVBA are performed and its phenomenal results derived using neighborhood awareness rate, execution time, the channel utilization rate and latency in warning message delivery with varying number of vehicular nodes are highlighted through Figs. 1, 2, 3 and 4 respectively. Figure 1 reveals that WIDVBA is

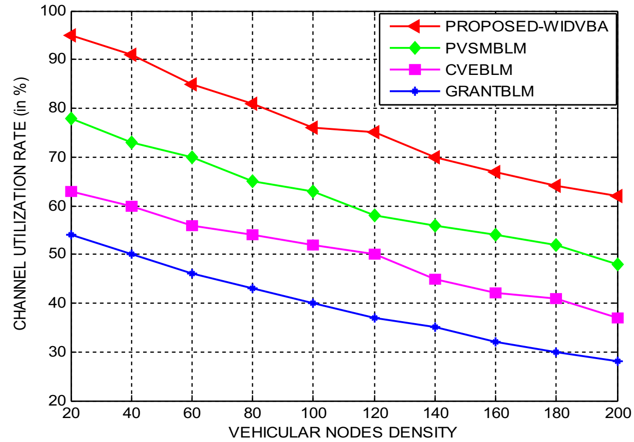

Fig. 3 WIDVBA-rate of channel utilization—vehicular node density

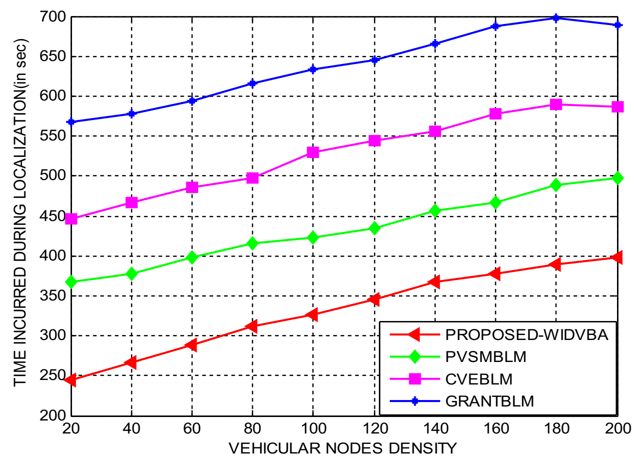

Fig. 4 WIDVBA-time cost in localizing NLOS nodes—vehicular node density

predominant in sustaining the rate of neighborhood awareness as the utilization of inertial weight into dynamic bat algorithm aids in maintaining the degree of awareness even when the number of vehicular density of the network increases proportionally. This maintenance of awareness rate by WIDVBA is also due to the regular updates in the frequency, position and velocity that helps to explore and exploit the location of the NLOS during data delivery. Thus the neighborhood awareness rate of WIDVBA is enhanced by 17%, 29% and 33% excellent to PVSMBLM, CVEBLM and GRANTBLM localization schemes.

Figure 2 spots out the performance of WIDVBA based on execution time that is evaluated under different vehicular densities. The execution time of WIDVBA is confirmed to be the least on par with the PVSMBLM, CVEBLM and GRANTBLM schemes. This reduction of execution time by WIDVBA is mainly due to the rate of exploration and exploitation which is adaptively varied depending on the affinity of the solution which is converging towards their optimal region. Thus the execution time of WIDVBA is reduced by 19%, 22% and 30% compared to PVSMBLM, CVEBLM and GRANTBLM localization schemes. Figure 3 emphasizes the performance of WIDVBA based on channel utilization rate evaluated under different vehicular densities. The channel utilization rate of WIDVBA is proved to be effective on par with the benchmarked schemes used for analysis. This impact on the channel utilization rate of WIDVBA is solely due to its potentiality in reliable maintenance of channel that prevents congestion during the connection established between the source and receiver of the emergency messages. The channel utilization rate of WIDVBA is estimated to be 31%, 34% and 38% superior to PVSMBLM, CVEBLM and GRANTBLM localization schemes.

Figure 4 quantifies the performance of WIDVBA based on time incurred in localizing NLOS nodes evaluated under different vehicular densities. The time incurred by WIDVBA in localizing maximum number NLOS nodes that are feasible under data forwarding is ensured to be dramatically reduced on par with the benchmarked schemes. This influential minimization in localization time of NLOS nodes is mainly due to the incorporation of self-learning factor that prevents the algorithm from trapping into a local optimum point of searching. Thus the time incurred in localizing NLOS nodes is predominantly reduced by 19%, 25% and 33% superior to PVSMBLM, CVEBLM and GRANTBLM localization techniques.

Further, Figs. 5 and 6 reveals the performance of WIDVBAin terms of neighborhood awareness rate and precision percentage compared to PVSMBLM, CVEBLM and GRANTBLM evaluated under a different number of NLOS nodes. Figure 5 confirms that the neighborhood awareness rate of WIDVBA is realized to be sustained even under an increased number of NLOS nodes in the network. This sustains in neighborhood awareness rate of WIDVBA is mainly due to the use of the exploration factor, which plays a vital role in effective localization of NLOS nodes. Thus the neighborhood awareness rate of WIDVBA analyzed with different NLOS nodes is proven to improve by 11%, 17% and 21% better to the compared PVSMBLM, CVEBLM and GRANTBLM schemes. Likewise, Fig. 6 glorifies the performance of WIDVBA in terms of precision percentage evaluated under a different number of NLOS nodes. The accuracy of WIDVBA is proved to be superior to the PVSMBLM, CVEBLM and GRANTBLM since the range of searching initiated by them gets dynamically increased and decreased based on an increase or decrease in the number of NLOS nodes that leads to less false positives. Hence the precision percentage of WIDVBA analyzed with different NLOS nodes is proven to improve by 8%, 13% and 17% better to the compared PVSMBLM, CVEBLM and GRANTBLM schemes.

Figures 7 and 8 proves the remarkable performance of WIDVBA compared to PVSMBLM, CVEBLM and

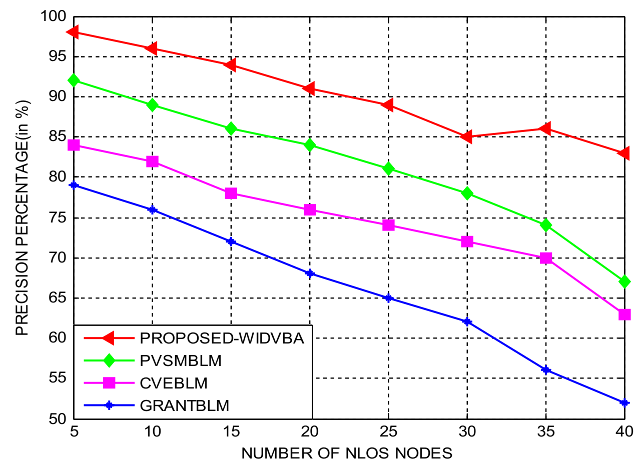

Fig. 6 WIDVBA-precision percentage—NLOS nodes

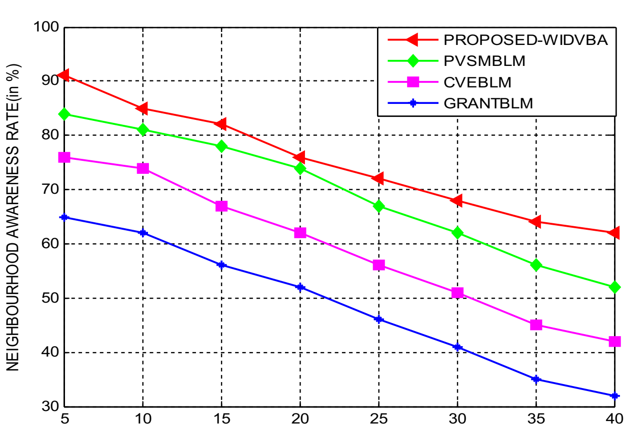

Fig. 5 WIDVBA-rate of neighbourhood awareness—NLOS nodes

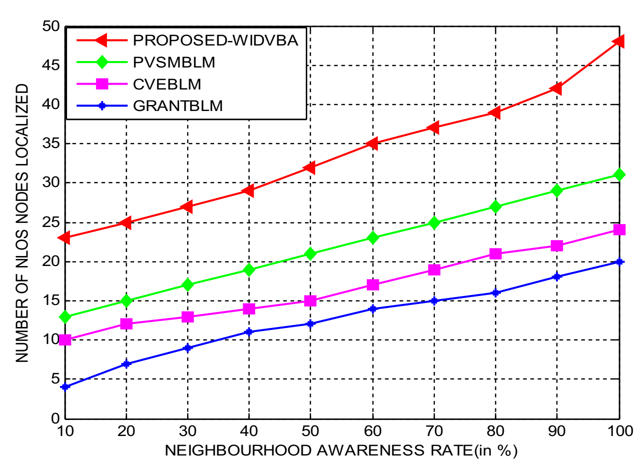

Fig. 7 WIDVBA-number of localized NLOS nodes—awareness rate

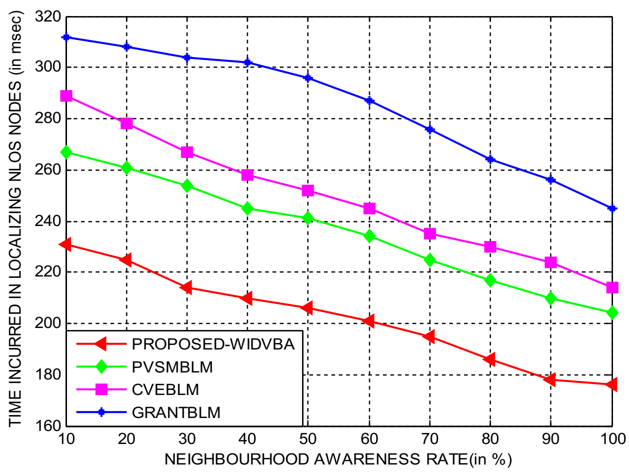

Fig. 8 WIDVBA-time cost in localizing NLOS nodes—awareness rate

GRANTBLM analyzed using numbers of localized NLOS nodes and time cost in localizing NLOS nodes under different awareness rate. The performance analysis of WIDVBA analyzed based on number of localized NLOS nodes with different awareness rate network seems to be phenomenally increased with a monotonic step increment of awareness rate since improvement in the awareness rate dramatically increases the rate of localizing NLOS nodes of the network. Figure 7 highlights that WIDVBA is excellent in localizing NLOS nodes compared to PVSMBLM, CVEBLM and GRANTBLM based on percentage improvement in the emergency message delivery rate, since the use of dynamic self-learning parameter and inertial weight parameter helps in improving the execution time and time incurred in detecting NLOS. The percentage improvement in the emergency message delivery rate of WIDVBA is confirmed to be improved by 8%, 21% and 35% on par with the compared PVSMBLM, CVEBLM and GRANTBLM. Figure 8 reveals that WIDVBA is predominant in improvising NLOS nodes' localizing rate compared to PVSMBLM, CVEBLM and GRANTBLM as the utilized exploitation is potential in controlling the velocity of the solution. The percentage in NLOS nodes' localizing rate of WIDVBA is ensured to be improved by 11%, 23% and 28% compared to PVSMBLM, CVEBLM and GRANTBLM localizing techniques.

Furthermore, Figs. 9 and 10 confirms the plots of WIDVBA analyzed using percentage improvement in the emergency message delivery rate and improvement in NLOS nodes' localizing rate. The plots provethat WIDVBA is excellent in maintaining the emergency message delivery rate and NLOS nodes localizing rate compared to PVSMBLM, CVEBLM and GRANTBLM techniques. This remarkable performance of WIDVBA is identified due to the faster execution time of the proposed algorithm that works optimally even when the number of NLOS are increased in the network. The overhead incurred in sustaining the rate of message delivery and localization also seems to be remarkable in WIDVBA. Thus the percentage improvement in the emergency message delivery rate of WIDVBA is confirmed to be improved by 10%, 13% and 16% better to the compared PVSMBLM, CVEBLM and GRANTBLM. Likewise, the

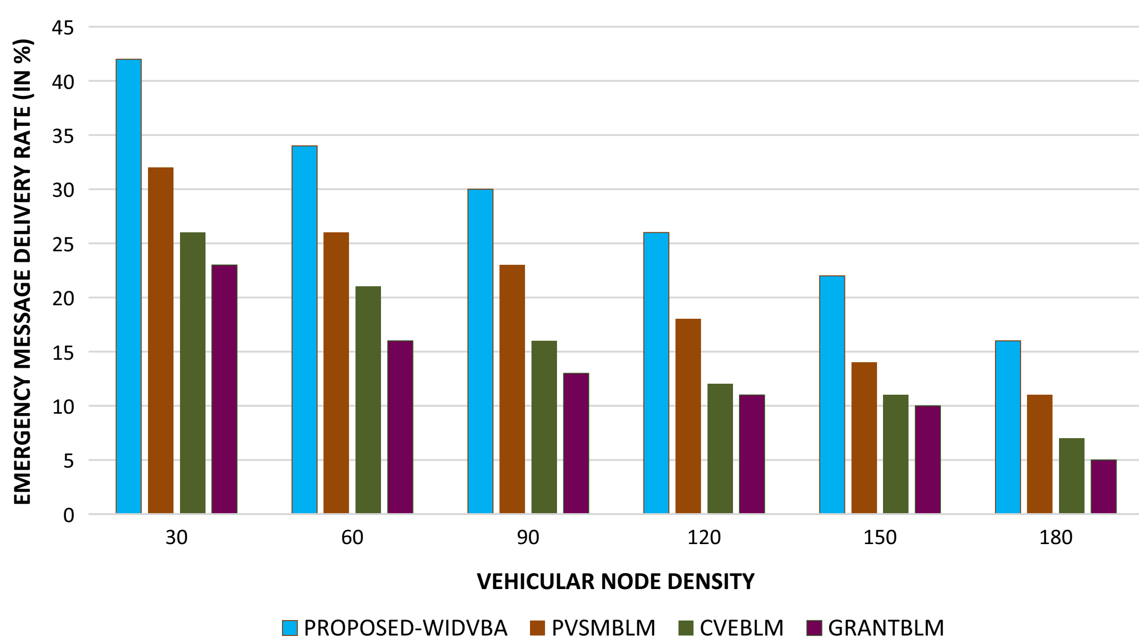

Fig. 9 WIDVBA-emergency message delivery rate under varying node density

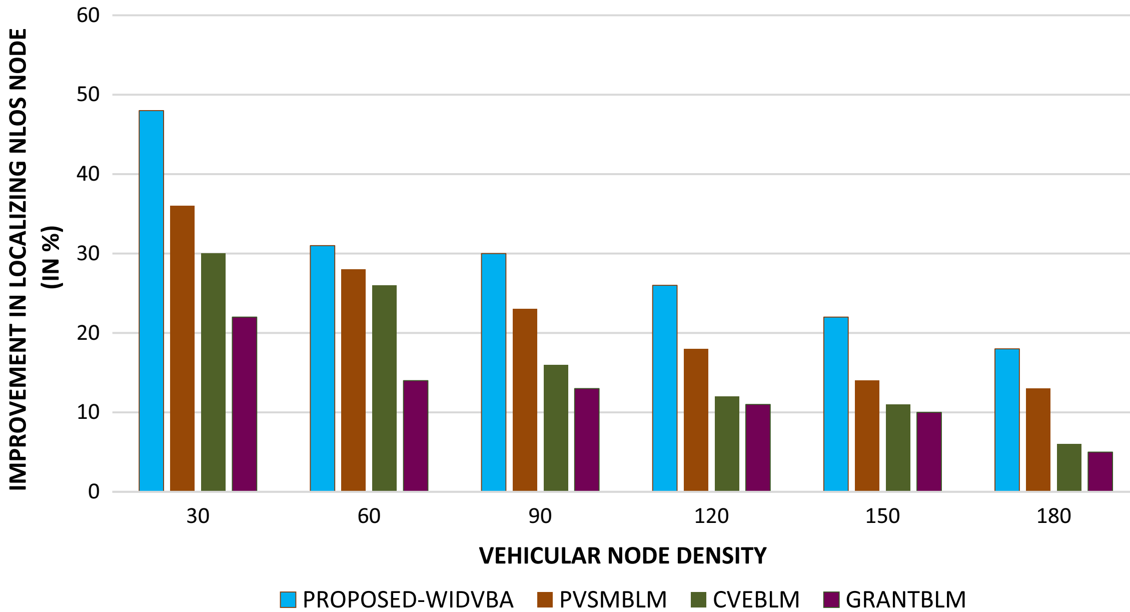

Fig. 10 WIDVBA-improvement in localizing rate of NLOS node–node density

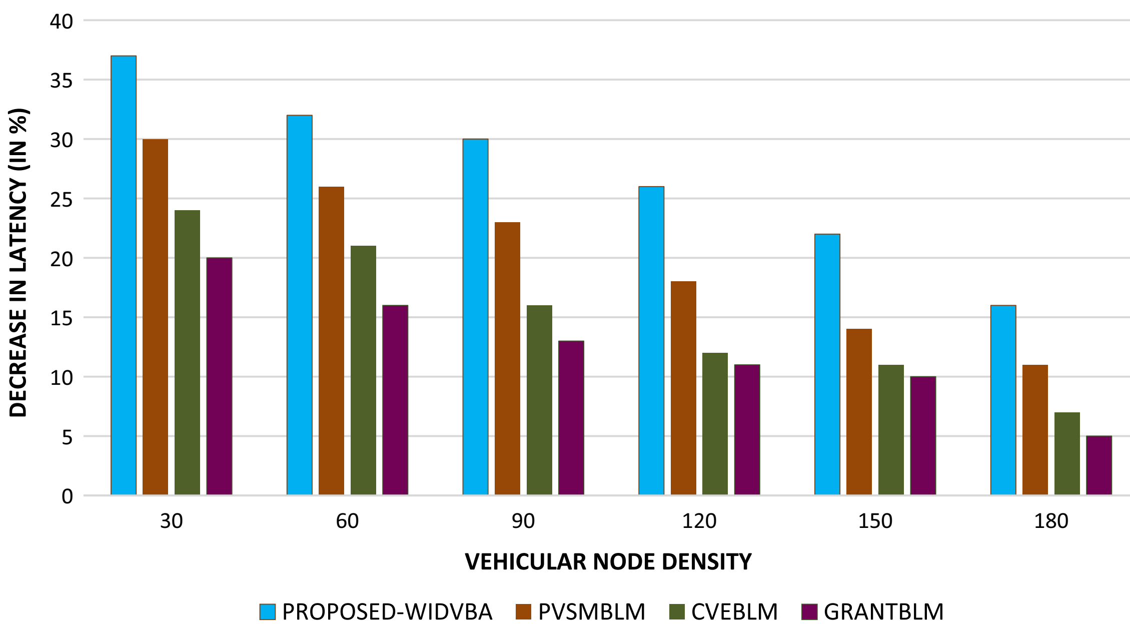

Fig. 11 WIDVBA-decrease in latency of emergency message-node density

localization rate of NLOS nodes are also determined to be improved by 7%, 11% and 13% superior to the benchmark mechanisms.

In addition, Figs. 11 and 12 glorifies the significance of WIDVBA over PVSMBLM, CVEBLM and GRANTBLM schemes evaluated under different node densities using percentage decrease in latency in emergency message delivery and percentage decrease in energy consumptions. This predominant reduction in latency and energy consumptions is mainly due to the faster execution rate which is dynamically increased based on velocity control exploitation factor used in this WIDVBA-based NLOS detection algorithm. The latency in the emergency message delivery of WIDVBAis determined to be reduced by 5%, 9% and 12% compared to the baseline NLOS localization schemes. Similarly, the energy consumptions incurred in localizing

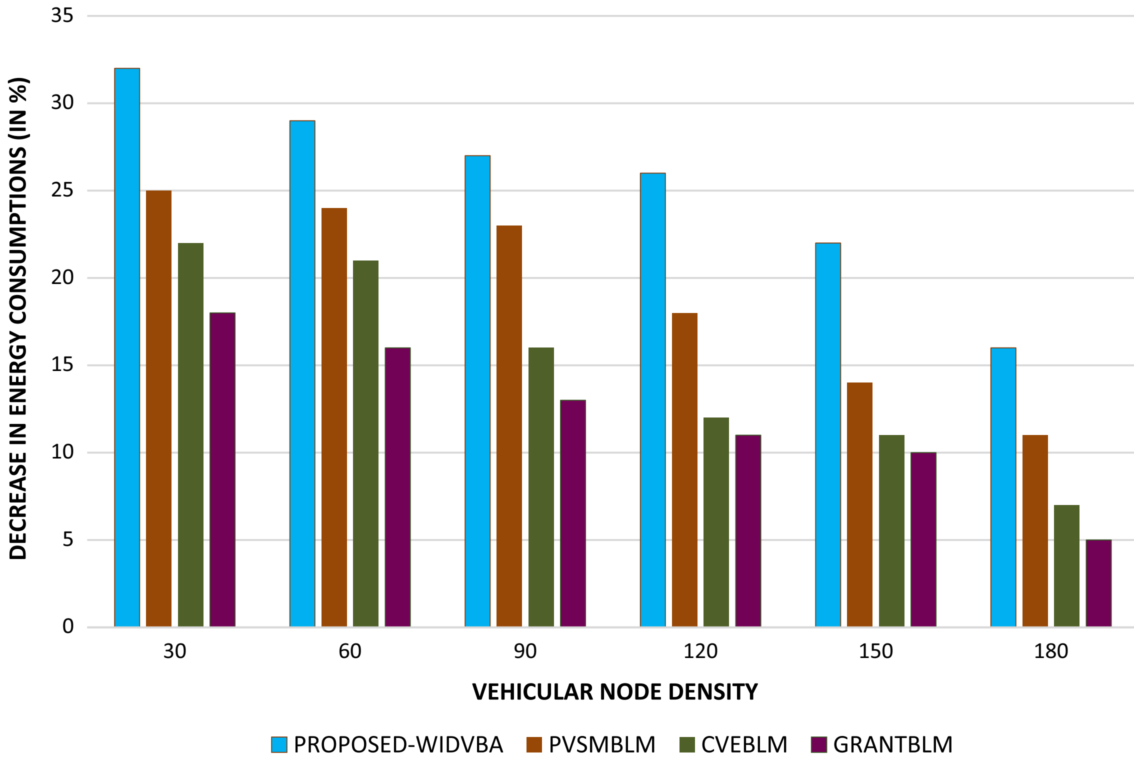

Fig. 12 WIDVBA-decrease in energy consumptions-node density

NLOS nodes are is also estimated to be decreased by 7%, 11% and 15% compared to the schemes considered for analysis.

5 Conclusion

WIDVBAis presented for minimizing the latency incurred in disseminating data among the vehicular nodes of the network by incorporating the merits of classical dynamic bat algorithm with inertial weight and PSO-SA based swarm intelligence. WIDBVA is confirmed to be effective as unnecessary exploration and exploitation of the search space is considerably reduced on par with the existing workof the literature. The simulation and empirical investigation of WIDVBA using EstiNet simulator confirms a mean neighborhood awareness rate and NLOS node localization rate of 18% and 24% superior to compared PVSMBLM, CVEBLM and GRANTBLM schemes. The latency and energy consumptions of WIDVBA evaluated under different vehicle densities also proveits phenomenal mean reduction of 15% and 23% compared to the NLOS localization approaches used for comparative analysis. In the future, it is planned to propose an inertial weight-based virtual binary bat algorithm for NLOS node localization.

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