[Iraqi Journal for Computer Science and Mathematics](https://ijcsm.researchcommons.org/ijcsm)

Volume 5 | Issue 4 Article 10

2024

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Recommended Citation

Rashid, Ahmed N. and Jubair, Ahmed Mahdi (2024) "Stable Heterogeneous Traffic Flow with Effective Localization and Path Planning in Wireless Network Connected and Automated Vehicles in~Internet of Vehicular Things (IoVT)," *Iraqi Journal for Computer Science and Mathematics*: Vol. 5: Iss. 4, Article 10.
DOI: https://doi.org/10.52866/2788-7421.1213
Available at: https://ijcsm.researchcommons.org/ijcsm/vol5/iss4/10

IRAQI JOURNAL FOR COMPUTER SCIENCE AND MATHEMATICS 2024;5:108–117

RESEARCH ARTICLE

Stable Heterogeneous Traffic Flow with Effective Localization and Path Planning in Wireless Network Connected and Automated Vehicles in Internet of Vehicular Things (IoVT)

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ABSTRACT

The increasing complexity of networks comprising both Connected Autonomous Vehicles (CAVs) and Human-Driven Vehicles (HDVs) presents substantial challenges in achieving accurate positioning, efficient communication, and optimal route planning. Current methodologies fall short in enhancing vehicular network efficiency and reliability due to noise interference, inefficient data transmission, and unstable data transfer. This study aims to improve localization accuracy, reduce communication noise, and enhance path planning efficiency in mixed CAV and HDV environments through the Stable Heterogeneous Traffic Flow using Deep Reinforcement Learning and Effective Path Planning (SHTDR-EPP) approach. The primary goals are to ensure dependable localization, efficient communication, and reliable route planning, thereby maintaining stable and efficient vehicle operations. The SHTDR-EPP approach integrates advanced techniques to analyze heterogeneous traffic flow. Firstly, effective localization is achieved among CAVs. Secondly, a deep reinforcement learning model is developed using the Markov Decision Process to manage mixed traffic flow efficiently. Thirdly, effective path planning is conducted using Extended Direction Analysis. These methods collectively ensure efficient communication between CAVs and HDVs. Experiments were conducted using NS3 and SUMO, with key parameters evaluated including vehicle delay, energy consumption, and safety metrics. The proposed SHTDR-EPP approach significantly enhances vehicular network performance. Positional accuracy is improved through effective localization techniques. Communication efficiency is increased by employing DRL to manage noise and stability. Path planning is optimized through EDA, ensuring efficient and reliable data transmission routes. Comparative analysis with prior methods such as OPP-CAVs and ROC-CAVs demonstrates that SHTDR-EPP achieves superior energy efficiency and vehicle safety. The SHTDR-EPP model effectively addresses critical issues of localization, communication noise, and path planning in mixed vehicular networks. By leveraging modern techniques, the proposed approach significantly enhances the overall efficiency, stability, and reliability of CAV and HDV interactions.

Keywords: Connected Automated Vehicles (CAVs), Intelligent Transportation Systems (ITS), Human Driven Vehicles (HDVs), Stable heterogeneous traffic flow, Deep reinforcement learning, Effective path planning

1. Introduction

The current development in intelligent transportation systems creates a way for the localization of Connected Autonomous Vehicles (CAVs), which are mainly utilized to control and manage the vehicles' traffic safety and high-speed mobility. Through CAV technology, traffic safety is highly improvised, reducing traffic congestion and increasing manufacturers' production. A recent study proves that around 90% of human errors during driving are rectified by using CAV technology [1]. The fact is that CAV technology

Received 8 June 2024; accepted 10 August 2024.
Available online 25 November 2024

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https://doi.org/10.52866/2788-7421.1213

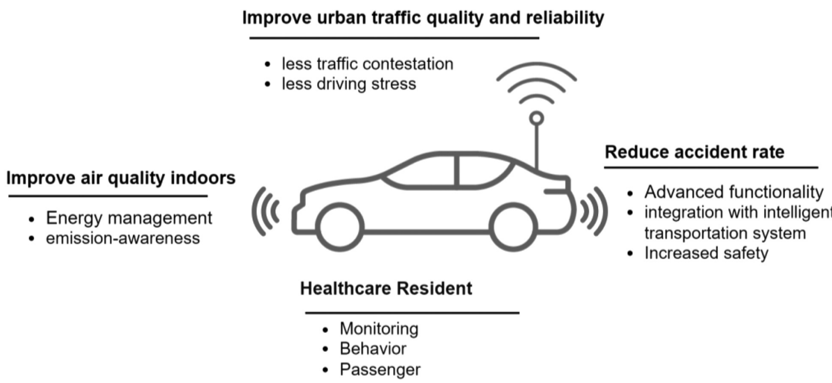

Fig. 1. Network structure of Connected and Automated Vehicle (CAV).

is still not perfectly adapted by real-world vehicular applications to control safety and mobility effectively. Then, the micro-simulation process is introduced to improve the benefits of CAVs in communication networks. The driving functionalities and characteristics of CAVs are dissimilar to humans, so they cannot handle any critical situation at the time of driving. In current real-life conditions, a CAV can only communicate with other vehicles in a fixed communication range, and multiple CAV connectivity is not appropriate similarly. Simulation data may not fully describe the complexity of real-world driving conditions. The study overlooks the possible cyber security risks associated with CAV and AV equipment [2]. The structure of a CAV is given in Fig. 1.

To improve the real-life CAV performance and to connect to multiple vehicles, the considered driving characteristics of the vehicles are their speed, velocity, location, and acceleration, surrounded by its DSRC (Dedicated Short-Range Communication) area. Currently, a maximum of drivers utilizes the automated features of cars while driving on the highways. The connectivity features are also improved, like “turned on” and “turned off,” which is purely automatic in CAVs [3, 4]. Focusing on a specific geographic area (SR417 in Orlando, Florida) may limit the generalizability of the results to other regions or traffic environments. Most of its functionality is derived from computer-generated models, but these may not always reflect the driving environment and behavior [5]. To reduce congestion in the CAV technology, collisions at recurrent motorway bottlenecks are concentrated, which mainly talks about diverges and weaves because it mainly reduces the network throughput and increases the delay, which directly becomes the major anxiety for the users. Car-following and lane-changing are other behaviors that affect the throughput performance. Countless earlier research concentrates on these issues to improve the throughput performance [6]. Study results are highly dependent on certain model parameters and prevalence rates, which may limit their generalizability. There is no mention in this document of the potential difficulties involved in deploying and integrating CAV technology into various transportation infrastructures [7]. At the current time, the improvement of stability and safety in CAVs has become an open research area, so several pieces of research have been done in this area to improve the benefits of effective traffic flow. The usage of CAVs has gradually increased compared with Human-driven vehicles (HDVs), which account for around 75% of global vehicle ownership. The traffic flow of the vehicles is currently at a mixed traffic flow of the HDVs and CAVs. In general, the speed of the CAVs is higher than the HDVs, so it is essential to monitor the network effectively [8]. Real-time healthcare applications may face significant delays and additional computational costs due to the implementation of blockchain technology. This can be problematic for many applications. The findings cannot be generalized to other medical data or Internet of things applications, as the study focuses on only two specific data sets. The lack of a comprehensive discussion on the implementation and maintenance of an effective blockchain-based cybersecurity framework in healthcare, as noted in the article, is due to time-consuming and multifaceted tasks [9].

The current traffic flow becomes highly heterogeneous, affecting the performance regarding the user understanding of an essential factor [9]. Real traffic conditions may be more complex and varied than what can be accurately estimated using numerical simulations. HDVs may exhibit a simple compensatory behavior that can lead to inaccurate results. Notably, the report does not address whether these proposed lane allocation strategies could be implemented effectively in existing and future traffic infrastructures [10]. Hence, heterogeneous traffic flow is the combination of both the HDVs and CAVs, which utilize various reaction times. The reaction time of CAVs is higher than that of HDVs, so it is essential to achieve an appropriate reaction time between the HDVs and CAVs to achieve effective vehicle-to-vehicle communication in the network. The approach's practical implementation may be constrained by its reliance on simulation outcomes, which does not validate it in a real-world WSN setup. The study neglects to fully compare the proposed hybrid method with other advanced energy-efficient clustering algorithms, apart from LEACH [11]. The hybrid method's performance is not adequately evaluated considering the presence of variable network conditions and scalability issues [12, 13]. Real-life traffic dynamics and potential communication failures may not be fully captured by simulations. Empirical validation of the proposed models and safety measures in real-world traffic scenarios is not present. The analysis overlooks the influence of varying environmental conditions and infrastructure variations on the effectiveness and safety of CAV and heavy vehicle cross-country operations [14]. This research article primarily concentrates on improving the stability of heterogeneous traffic flow with the combination of HDVs and CAVs.

The major drawbacks of CAVs are analyzed with the help of earlier research. The problems identified in CAVs are stability and safety improvisation among the vehicles and a proper communication building among the HDVs and CAVs to achieve effective communication among the vehicles from various categories. Consequently, effective, and stable path planning becomes more crucial to accomplish this task. To increase the efficiency and constancy of the heterogeneous vehicular communication, which consists of connected and non-connected automated vehicles, EPP between them needs improvement, and the trajectories of the CAVs need to be concentrated. There is a lack of research on the effectiveness of the method in dealing with highly dynamic or severe traffic conditions, and there is no consideration of how the localization process is affected by sensor errors and variable data quality. The lack of exploration on integration with real V2X systems and scalability to accommodate larger fleets is also an issue. Variable sensor noise and interference have an impact on the proposed localization method. Furthermore, it does not prove the effectiveness of this method in extremely dynamic or complex traffic situations other than simulation. The contribution of the research is described below:

- The current generation of vehicular communication combines CAVs and HDVs. To improve the stability and connectivity of the CAVs to HDVs and HDVs to CAVs communication, a novel framework is developed that concentrates on the optimization of the whole mixed traffic flow of the CAVs called Stable Heterogeneous Traffic Flow using Deep Reinforcement Learning (SHTDR) with Effective Path Planning (EPP) among the connected and non-connected automated vehicles.
- Parameters such as relative Direction-of-Arrival (DOA) and Relative Distance (RD) are considered at the initial condition to achieve effective localization. Through these parameters, an effective vehicle deployment is performed among the CAVs. In addition, it also increases the vehicle-to-vehicle communication quality.
- The SHTDR method works through Deep Reinforcement Learning using MDP, and the EPP method works through the Extended Direction algorithm (EDA). To achieve normalized traffic flow among the CAVs and HDVs, the response time of the CAVs is degraded, which helps to achieve linear stability among the vehicles. These two methods are effective enough to improve connectivity and stability among the CAVs and HDVs.

The organization of the paper is Section 2 is discussed the related works of the previous fault and losses. Section 3 is a construct SHTDR-EPP proposed model which was developed from existing models. Section 4 discusses the simulation results to compare the previous models and shows the SHTDR-EPP model is better than the existing model. Section 5 is the conclusion of the study.

2. Related works

Several earlier studies have been developed in the context of Wireless Network Connected and Automated Vehicles within internet of vehicles things. This section discusses some of these significant studies. They include: The authors in [15], to solve the System-Optimal Dynamic Traffic Assignment (SO-DTA) problem with vehicle-exclusive lane segments, the author Haiyang Liu et al. proposed a cell transmission model for separate vehicle and bus traffic (CTM-SCB) for analysing the network performance of XBLs and IBLs and optimizing the network-wide configurations for future urban traffic networks. The effectiveness of the network is significantly increased by the proposed method. In [16], a route generation methodology of an Enhanced Driver Model and a Dynamic Programming based algorithm is developed to build a variety of simulated vehicle journeys and synthetic paths for large-scale CAV energy usage assessment. The extracted real-world routes from open-source mapping tools can then be compared to the produced simulated routes in terms of their characteristics. In [17], a decentralized method for optimizing the paths of CAVs is proposed in both the longitudinal and transverse directions along a signalized highway where both human-driven and autonomous vehicles CAVs coexist. A two-stage model is created to maximize CAV paths based on traffic light plans of downstream junctions and trajectory data of nearby cars. The proposed model can decrease CAVs average delay times.

In [18], the predictive control (MPC)-based approach is embedded within the Aimsun microsimulation platform, which permits the assessment of numerous genuine vehicles' operating and progression situations under various vehicle combinations. Due to better real-time knowledge and short-term projection from V2V contact, linked controlled vehicles appear more effective at reaching their desired pace than non-connected controlled vehicles. In [19], it has provided a solution to the resilient optimum control issue for linked and autonomous vehicle platoons concurrently prone to unclear parasitic actuation latency and input delays. An improved multi-agent-based particle swarm optimization algorithm is used to find the optimal design parameters in the derived stability region to minimize a weighted objective function for the robust optimal problem. In [20] suggests a technique that defines successive HDVs (i.e., AHDV) to minimize HDV stochasticity and uses its prominent characteristics to regulate the CAVs. The results show that the proposed control method performs well in oscillatory reduction, eco-driving, and generalization.

In [21], the general model framework of the fundamental diagram of the mixed traffic flow is proposed. Under critical conditions, the influence factors of the fundamental diagram are addressed. Finally, the general condition of stable mixed-traffic flow is devised, taking platoon size and CAV density into account. This method enhances the influence of the characteristics of the CAV platoon on stability. In [22], the impact of the maximum platoon size of CAVs on traffic safety in mixed-mode traffic is investigated. The intelligent driver model (IDM), gap-regulating model, coordinated adaptive cruise control (CACC), and Adaptive Cruise Control (ACC) models represent the four vehicle-following modes. CAV entry rate affects the effect of platoon size on mixed traffic flow safety. In [23], a combined receding horizon framework control framework for traffic signal optimization is developed, and CAV nanoscale control at an isolated signalized junction to reduce fuel usage and enhance transportation sustainability. The combined traffic control system can boost traffic and energy economy. [24] provided an accurate and stable iterated split covariance intersection filter (Iterated Split CIF)-based cooperative localization approach with a decentralized structure that can assure efficiency when data sources have multiple error types. Using neighbour vehicle information, we use an efficient point cloud registration method to estimate cooperative relative pose.

[25] developed an Extended Kalman Filter-based joint tracking method to handle inaccurate GPS position data. It centralizes and distributes multi-modal fusion is developed. The graph Laplacian operator encodes range and GPS data linearly using the network layout of working vehicles. The expanded trial assessment using realistic vehicle paths derived by VEHICLELA automated driving software shows substantial GPS error reduction under natural conditions. [26] presented a cooperative localization method that conducts multi-modal-fusion between linked vehicles by modelling a fleet of connected vehicles as an undirected graph, storing each vehicle location relative to its neighbours. This method uses Laplacian Processing and temporal coherence from vehicle motion patterns. This reduces the GPS MSLE. [27] proposed a joint localization method using relative DOA and RD to enhance CAV localization accuracy in multivehicle environments, which improves vehicle location accuracy.

3. Proposed SHTDR-EPP approach

To achieve precise CAV and HDV localization, the proposed SHTDR-EPP model employs a robust localization model that incorporates GPS measurements and Gaussian noise measurement, while also providing an efficient Markov decision-based DRL approach to reduce noise and improve communication efficiency. The implementation of EPP through EDA promotes better vehicle trajectories and reduces cost functions to facilitate efficient data transmission. Dynamic mobility analysis is used to continuously evaluate trajectories, aiding in efficient route planning, and increasing communication stability and reliability between vehicles by evaluating trust points based on cost efficiency and optimal costs. The workflow of the proposed approach is illustrated in Fig. 2.

At the initial condition, the three-dimensional positioning error model is developed in the place of the host vehicle, which collects the data of the neighbor vehicles by considering the azimuth angle and pitch angle, including the inter-vehicular distance at the time of establishment of vehicle-to-vehicle data transmission. Then, deep reinforcement learning is

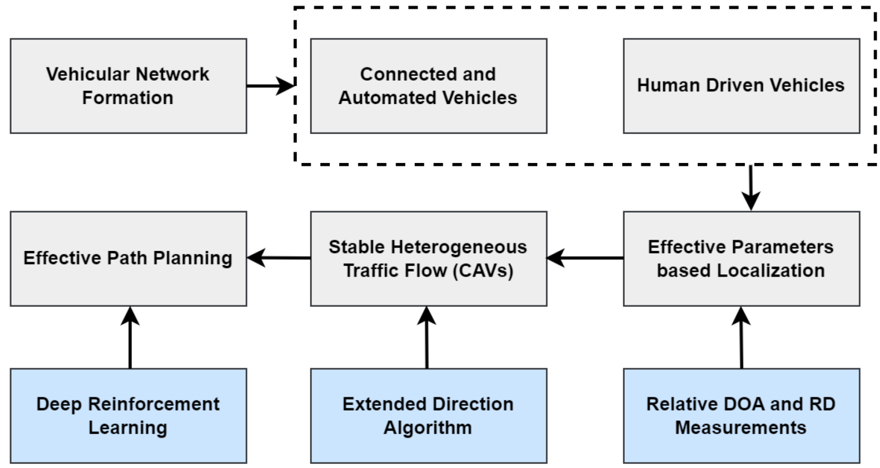

Fig. 2. Workflow of the proposed approach.

the process of creating a new control strategy using the Markov Decision Process (MDP) to neglect the disturbances during data transmission among the CAVs and HDVs. To achieve effective communication among the vehicles, the generation of a short-term path becomes essential, and for that purpose, an Extended Direction algorithm (EDA) algorithm is developed to ensure high-quality communication among the vehicles. The EDA model is a MAC-based approach mainly concentrating on the link layer. Regarding heterogeneous traffic flow among the CAVs and HDVs, the communication among various vehicles is handled in the following cases. There are: (i) communication between two CAVs, in which the CAV follows another CAV for data exchange; (ii) communication between CAVs to HDVs where the CAVs follow the HDV for data exchange; (iii) the communication between the HDVs where the HDV follow another HAV to exchange the data and (iv) the communication between HDV to CAVs where the HDV follows CAVs to exchange the information. Finally, the ratio of the different vehicle types is analyzed using the probabilistic theory. Algorithm 1, Effective Communication and Path Generation in CAVs and HDVs.

3.1. Stable localization model

At each instant of time $t(t = 1, ..T)$, e set taken for vehicular network analysis $G^{(t)} := \{G_1^{(t)}, \ldots, G_v^{(t)}\}$. The number of CAVs considered is represented as v in a certain group of vehicles called cluster. Inside the cluster $|G_v^{(t)}|$ where its value is 3, the CAVs and HDVs are resent here, and it perform an exchange of information. The present state of the v-th Vehicular with the time of t is represented as $p_i^{(t)} = [x_i^{(t)} y_i^{(t)}]^T \in R^2$ where the distance is measured according to the following expression (1), which is equal to $z_{d,i,j}^{(t)} = \|p_i^{(t)} - p_j^{(t)}\|$.

$$z_{az,v1,v2}^{(t)} = \begin{cases} \lambda\pi + \arctan \frac{\left|x_{v2}^{(t)} - x_{v1}^{(t)}\right|}{\left|y_{v2}^{(t)} - y_{v1}^{(t)}\right|}, \lambda = 0, 1 \\ \pi + \arctan \frac{\left|y_j^{(t)} - y_i^{(t)}\right|}{\left|x_{v2}^{(t)} - x_{v1}^{(t)}\right|}, \lambda = \frac{1}{2}, \frac{3}{2} \end{cases} \tag{1}$$

The CAVs and HDVs are equipped with GPS to provide their location and other vehicle measurements, which are performed using the Gaussian measurement noise. Following that, three measures are calculated for all the vehicles they are with $\zeta(\mu, \Sigma)$ as the Gaussian distribution and μ, Σ its mean and covariance, Σ_p. Is a diagonal matrix equal to $\mathrm{diag}(\sigma_x^2, \sigma_y^2)$. The considered measurements are given in Table 1.

Furthermore, the Laplacian matrix is considered to locate the vehicle $L^{(t)} \in R^{|G_{v1}^{(t)}| \times |G_{v1}^{(t)}|}$s $L^{(t)} = D^{(t)} - A^{(t)}$, where $D^{(t)}$ and $A^{(t)}$ are the degree and the adjacent side of the vehicle. The differential coordinates according to the vehicle location are represented as $\delta_i^{(t)} = [\delta_{v1}^{(t,x)} \delta_{v1}^{(t,y)}] \in \mathrm{R}^2$ are equal to $\delta_{v1}^{(t,x)}$ and $\delta_{v1}^{(t,y)}$ as well the mathematical expression for those values is given in Eqs. (2) and (3).

$$\delta_{v1}^{(t,x)} = \frac{1}{\left|N_{v1}^{(t)}\right| - 1} \sum_{j \in N_{v1}^{(t)}} \left(-\tilde{\mathbf{z}}_{d,v1v2}^{(t)} \sin \tilde{z}_{az,v1v2}^{(t)}\right) \tag{2}$$

$$\delta_{v1}^{(t,x)} = \frac{1}{\left|N_{v1}^{(t)}\right| - 1} \sum_{j \in N_{v1}^{(t)}} \left(-\tilde{\mathbf{z}}_{d,v1v2}^{(t)} \cos \tilde{\mathbf{z}}_{az,v1v2}^{(t)}\right) \tag{3}$$

where $N_{v1}^{(t)}$ implies the current vehicle neighbour with cardinality $N_v^{(t)}$. The Laplacian matrix is expressed

Algorithm 1. Focuses on communication and path creation in CAV and HDV.

Step 1. Initialization includes the gathering of initial data, 3D position information for the host vehicle, and information about nearby vehicles such as their azimuth angle, elevation perspective, or vehicle distance. Additionally, physical measurements are taken.
Step 2. Produce a positioning error model and construct another 3D positioning error model for the host vehicle's location, considering both its azimuth angle and elevation angle information, and adding up to calculate how many miles are between vehicles in this error modeling method.
Step 3. Commence V2V communication based on the positioning error model.
Step 4. Utilize Deep Reinforcement Learning and DRL to create a novel control strategy and implement Markov Decision. A process (MDP) that deals with interference during data transmission between CAV and HDV devices.
Step 5. Formulate a short-term trajectory devise an EDA to guarantee excellent vehicle communication, and facilitate the EDA model as a MAC-based approach that focuses on the link layer.
Step 6. Handle heterogeneous traffic flow, and handle communication in the following situations:

Case 1: CAV-CAV communication, CAV follows another CAV communication.
Case 2: CAV-HDV communication, CAV follows HDV in communication.
Case 3: Data transfer from HDV to HDV, HDV follows another HDV in data exchange.
Case 4: HDV-CAV communication, HDV follows CAV in communication.

Step 7. Evaluate the proportions of different vehicle types (CAV and HDV) using probability theory.
Step 8. Emphasize superior communications quality, optimize data transfer, and constantly adjust the EDA system to ensure efficient communication between vehicles.
Step 9. This is the end of the algorithm.

Table 1. Measurements and expression.

Measurement	Expressions
Absolute position measurement	$\tilde{\mathbf{z}}^{(t)}_{p,v1} = p^{(t)}_{v1} + n^{(t)}_{p}, n^{(t)}_{p} \sim \zeta(0, \Sigma_p)$
Distance measurement	$\tilde{\mathbf{z}}^{(t)}_{az.v1v2} = z^{(t)}_{az.v1v2} + n^{(t)}_{az}, n^{(t)}_{az} \sim \zeta\left(0, \sigma^2_{az}\right)$
Azimuth Angle measurement	$\tilde{z}^{(t)}_{az.v1v2} = z^{(t)}_{az.v1v2} + n^{(t)}_{az}, n^{(t)}_{az} \sim \zeta\left(0, \sigma^2_{az}\right)$

as $L^{(t)} \in R^{2|G^{(t)}_{v1}||G^{(t)}_{v1}|}$ with the vector $b^{t,x} \in R^{2|G^{(t)}_{v1}|}s$ $b^{t,x} = [\frac{D^{(t)}g^{(t,x)}}{\tilde{z}^{(t,x)}_{p}}]$. ere $\delta^{(t,x)} \in R^{|G^{(t)}_{v1}|}$. To consider the vehicles, positions $b^{t,x}$ s calculated, and it is expressed as equation below (4).

$$L^{(t)}x^{(t)} = b^{(t,x)}. \tag{4}$$

According to these calculations, the x and y positions of the CAVs and HDVs are identified, which helps to achieve effective localization among the vehicles.

3.2. Deep Reinforcement Learning (DRL) methods

Mainly to reduce the noise factor that is created at the time of communication between the CAVs and HDVs, this DRL method is created, which is designed based on the Markov Decision Method (MDM). This method contains four different factors for the analysis: location (L), activity (A), principles (P), and rewards (R). Here, the term location implies the vehicle data fusion, which includes the weighted deviations among the distance (ΔDis^t_v) and vehicle mobility (Δsp^t_v), and the location calculation is mathematically expressed as $L^t_v = [\Delta Dis^t_v, \Delta sp^t_v]$. The location calculation is performed at each instant of time as per the movements of the CAVs and HDVs. The principles for communication are created according to an implicit function related to the location and activities so that it becomes P(A|L), which is updated periodically to achieve effective performance among the vehicles. Finally, rewards are determined where the vehicle follows controlled efficiency that treats the CAVs in a trained equilibrium state to achieve highly flexible communication. According to these parameters, the cost efficiency of the vehicle is decided, which is mathematically expressed in the equation below.

$$CE^t_v = \left(L^t_v\right)^T M_v * L^t_v \tag{5}$$

In the above equation, the term M_v plies the matrix in diagonal coefficient where M_v s mathematically expressed below.

$$M_v = [a_{L,v}\ a_{z,v}] \tag{6}$$

In Eq. (6), the weights of $a_{1,v}0$ and $a_{2,v} > 0$. This finally results in the optimal cost, which is mainly designed to improve the vehicle stability, is expressed in Eq. (7).

$$OC^t_v = a_{z,v}\left(a^t_v\right)^2 \tag{7}$$

In Eq. (7) the term $a_{3,v}$ plies the weight of vehicle handling, calculated among the CAVs and HDVs. The final trust score is measured using the vehicle's cost efficiency and optimal cost, and the mathematical expression for the trust value is given in Eq. (8).

$$T^t_v = CE^t_v + OC^t_v. \tag{8}$$

According to this trust calculation process, the data transmission among the vehicles is effectively handled, leading to improving the communication stability of the vehicles.

3.3. Effective Path Planning (EPP) model

The algorithm that is used for the process of EPP is Extended Direction Analysis (EDA), which mainly concentrates on reducing the vehicles' cost functions. At the initial stage, the vehicles' trajectories are analyzed where $T(v), v = 0 \ldots, (v-1)$.,nd kept in correspondence with the cost function. Currently, the extended directional equation is mathematically expressed in the equation below.

$$EDA_v = \left[\frac{\delta CF}{\delta T(v)}\right] \rho(v+1) + \frac{\delta \varphi}{\delta T(v)} \tag{9}$$

According to this equation, the control space is achieved among the dynamic mobility-based vehicles. This calculation is performed at each instant of time to select the effective path among the vehicles to transmit the data between the sources to the destination. Table 2, shows the difference between the three proposed models.

4. Simulation evaluations

This section evaluates the effectiveness of the proposed SHTDR-EPP approach, where the implementation and evaluation are conducted using NS3 and SUMO mobility generators, which are open-source, highly flexible simulators. SUMO is mainly chosen to identify the vehicle communication model and lane-changing process. The parameters that are concentrated to analyze the performance are vehicle delay, vehicle energy, and vehicle safety measurements. The calculated results are compared with the earlier methods like OPP-CAVs [18] and ROC-CAVs [19].

4.1. Vehicle delay calculation

Vehicle delay is defined as the extra time taken to transmit the data from one place to another among the CAVs and HDVs. Generating a lower range of delay leads to better performance in vehicular networks. In Fig. 3, the vehicle's delay analysis is graphically represented, where the performances of OPP-CAVs, ROC-CAVs, and SHTDR-EPP approach are given. With the help of effective localization and path selection process using the DRL method, the performance of the proposed SHTDR-EPP approach is better than the others.

Table 2. Explanation of differences between the three proposed models.

Feature/Aspect	Stable localization Model	Deep Reinforcement Learning Methods	Effective Path Planning Model
Primary Objective	Precise localization of CAVs and HDVs	Reduce communication noise and improve decision-making for efficient communication.	Optimize vehicle trajectories and reduce cost functions for efficient data transmission.
Core Components	GPS measurements, Gaussian noise measurement, Laplacian matrix	MDP, location (L), activity (A), principles (P), rewards (R)	EDA, dynamic mobility analysis
Measurement Techniques	Absolute position, distance, azimuth angle measurements	Weighted deviations, vehicle mobility, implicit functions for principles	Trajectory analysis, dynamic mobility, control space calculations
Mathematical Models Used	Gaussian distribution, Laplacian matrix, differential coordinates	MDP, cost-efficient, optimal cost, trust score	Extended directional equation, cost function correspondence
Communication Efficiency	Enhances communication stability and reliability	Improves communication by reducing noise and optimizing decision-making	Focuses on efficient data transmission through optimal path selection
Data Handling	Incorporates real-time GPS data and physical measurements	Fusion of vehicle data considering location and activity	Trajectories analyzed in real-time to determine effective data paths
Trust Evaluation	Based on Cost efficiency and optimal cost	Archived through a reward system and trained equilibrium states	Not specifically focused on trust evaluation but on trajectory and cost optimization
Implementation Complexity	Moderate (requires integration of GPS and noise measurement systems)	High (involves complex DRL algorithms and continuous learning)	Moderate (focuses on trajectory analysis and optimization, requires EDA implementation)
Key Benefit	Accurate localization of vehicles for better communication	Enhanced communication efficiency and noise reduction	Efficient data transmission with optimized paths and reduced costs

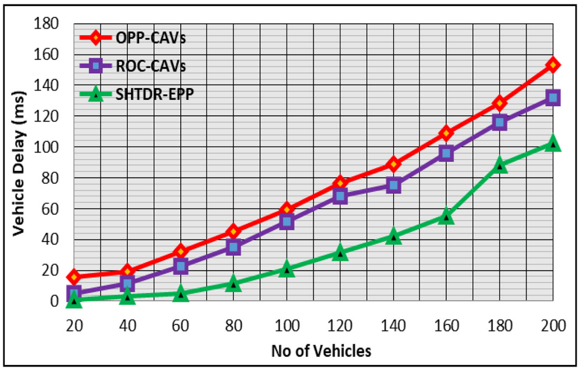

Fig. 3. Vehicle delay calculation.

4.2. Vehicle energy calculation

The vehicle's energy is measured in the way that the remaining energy is stored at the end of the simulation, and if the percentage of energy stored in the vehicles is high, that leads to an increase in the overall energy efficiency of the network. In Fig. 4, the vehicle's energy of the proposed SHTDR-EPP approach is calculated and compared to the earlier methods like OPP-CAVs and ROC-CAVs. The power utilization is highly reduced in the proposed SHTDR-EPP, which is achieved with the help of effective path selection and localization processes among the vehicles.

4.3. Vehicle safety measurements calculation

The vehicles are allowed to communicate with other CAVs and HDVs, so it needs to concentrate more on data confidentiality. To achieve effective communication, attaining a maximum percentage of vehicle safety is indispensable. In Fig. 5, the calculation of vehicle safety is performed among the methods like OPP-CAVs, ROC-CAVs, and SHTDR-EPP from that the proposed SHTDR-EPP achieved better performance with the help of the induced ideas like effective path selection and noise reduction.

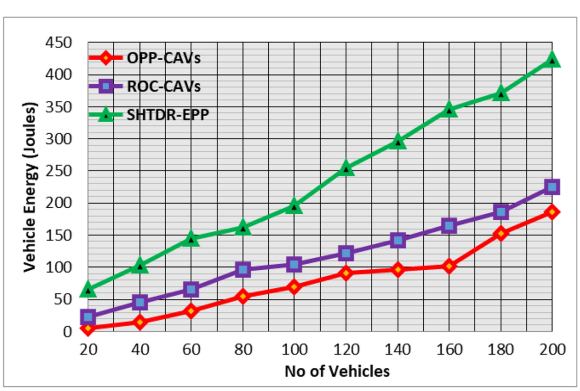

Fig. 4. Vehicle energy calculation.

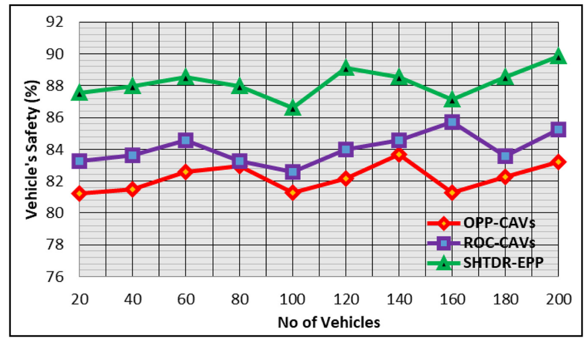

Fig. 5. Vehicle safety measurements calculation.

Table 3. Results analysis and measurements.

Parameters/Methods	OPP-CAVs	ROC-CAVs	SHTDR-EPP
Vehicle Delay	153.26 ms	131.75 ms	102.48 ms
Vehicle Energy	186.28 Joules	225.17 Joules	423.28 Joules
Vehicle Safety	83.23%	85.23%	89.85%

Table 3 provides the performance analysis of the considered methods like OPP-CAVs, ROC-CAVs, and SHTDR-EPP in terms of vehicle delay, vehicle energy, and vehicle safety measurements. The vehicle delay proposed by the earlier methods OPP-CAVs and ROC-CAVs are 153.26 ms and 131.75 ms, respectively, but the proffered SHTDR-EPP produced around 100 ms, which is 30 ms to 50 ms lower than the earlier methods. The vehicle's energy attained by the OPP-CAVs and ROC-CAVs are 186.28 Joules and 225.17 Joules, whereas the proffered SHTDR-EPP attained 423.28 Joules, which is 200 to 250 joules higher than the earlier methods. In terms of vehicle safety measures, the proposed SHTDR-EPP attained 89.85%, but the earlier methods, OPP-CAVs, and ROC-CAVs, attained 83.23% and 85.23%, respectively. So, the vehicle safety achieved by the proposed work is 4% to 6% higher than the earlier methods. Ideas like effective path selection among the CAVs and HDVs, noise avoidance, and effective localization in the proposed SHTDR-EPP lead to achieving better performance among the vehicular networks.

5. Conclusion

A novel approach is developed to improve the localization and communication among the CAVs and HDVs, namely the SHTDR-EPP, which helps achieve intelligent communication. This proposed method combines certain processes like the stable localization model, DRL method, and effective path planning model. This method allows noise reduction and delay reduction among the vehicles. The implementation of the proposed SHTDR-EPP is done in NS3 and SUMO, as the output values are calculated for parameters like vehicle delay, vehicle energy, and vehicle safety measurements, where it gets compared with the previous research like OPP-CAVs and ROC-CAVs. The results show that the proposed SHTDR-EPP achieved a 6% high vehicle safety ratio, 250 joules, high energy efficiency, and around 50 ms minimum vehicle delay compared with the earlier methods. In the future direction, drones will be involved to enhance the network density and vehicle coverage.

Funding

There is no fund for this research.

Conflicts of interest

The authors declare that there is no conflict-of-interest statement.

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