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Jacobian linear regression and Tate Bryant Euler angle enabled autonomous vehicle LiFi communication sustained IOT

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ABSTRACT
Artificial Intelligence (AI) and the constant paradigm shift in road traffic have led to a need for significant improvement in road safety to minimize traffic accidents. LiFi helps minimize accidents by transmitting data between multiple vehicles (i.e. Vehicle-to-Vehicle (V2V)) and between vehicles and infrastructure (i.e. Vehicle-to-Infrastructure (V2I)) without interference. LiFi uses light to transmit data between devices or vehicles, which ensures efficient data transmission speed and is therefore considered a safe technology. A method called Deep Jacobian Regression and Tate Bryant Euler Recommendation (DJR-TBER) is proposed in this paper based on V2V and V2I autonomous vehicle communication. The proposed method DJR-TBER consists of an input layer, four hidden layers and finally an output layer. Sensors are first used to obtain the information. A linear regression-based speed evaluation model is developed and followed by a Jacobi matrix-based distance evaluation model in the hidden layer. The third hidden layer by developing a distance evaluation model. The use of Laplacian function ensures secure V2I communication for the autonomous vehicle. Finally, a Tate-Bryant-Euler angle-based model for emergency handling is proposed in the hidden layer to optimally consider the aspect of braking in emergency situations and thus increase driving safety.

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1. Introduction

Over the past few years, traffic congestion has been considered as a problem to be addressed. With the evolution of Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, autonomous vehicles possess the potentiality to circumvent traffic congestion and enhance efficiency in traffic. However, two important aspects that play major role are consistency and reliability for maintaining safety and security of autonomous vehicle. Nevertheless, this weakness of autonomous vehicles makes them tremendously susceptible to several security and safety issues.

A scheduling scheme for autonomous vehicles was proposed in [1] integrating outflow traffic and fairness analysis. To achieve this, a multi-objective function that ensures both outflow traffic maximization and fairness was first designed. Also as numerous vehicles pass a highway on-ramp with the increase in the outflow traffic, the proposed scheme reduced vehicle density on the other hand by increasing the outflow traffic. Moreover, it also distributed vehicle density on both the main and ramp roads by fair assignment of merging times, therefore reducing the average travel time of vehicles. Despite minimizing the average vehicle travel time, the collision involved during the autonomous vehicle highway merging was not focused.

A New Adversarial Deep Reinforcement Learning (NDRL) method was proposed in [2] for ensuring safety and security. In this method, the attacker-autonomous vehicle action-reaction is analysed via game theory formulation by incorporating deep learning. Each autonomous vehicle employed Long-Short-Term-Memory (LSTM)-Generative Adversarial Network (GAN) to identify the probable distance variation and provided this as input to NDRL that in turn minimized the distance variation and therefore ensuring safety and security. Despite providing mechanisms for safety and security, only the relative distance or relative speed between vehicles were utilized as the judgment benchmark for making vehicle control decision. However, in case of emergency solutions were not provided.

In [3], Eco Driving mechanism was formulated by integrating target vehicle speed by means of Dynamic Programming (DP) to obtain the optimal speed. Moreover, encoder-decoder architecture was also proposed with the purpose of analysing target vehicle patterns using a Gated-Recurrent-Unit (GRU), therefore improving predictor accuracy.

Several evolutionary functions of involved vehicles depend on information obtained wirelessly with other vehicles and roadside infrastructure. An investigation of 5G millimeter-wave communication links was

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designed in [4] for low-speed autonomous vehicle, concentrating on the influences of positioning of antenna on both received signal quality and link performance. An elaborate design, planning and control of AV were discussed in [5]. Current challenges faced by AV and the probable future directions were investigated in [6].

The key problem with these above-mentioned security solutions is that they do not consider the collision involved between V2V and V2I of autonomous vehicle while formulating the security and safety resolution. Additionally, there is no proper work in modelling the emergency situations for LiFi traffic monitoring communication system. In fact taking into account the collision rate and emergency situations into focus will enable us to provide better security and safety mechanism. Thus, an efficient safety and security method for autonomous vehicles with Lifi communication sustained IoT for V2V and V2I autonomous vehicle communication is the need of hour.

1.1. Contributory remarks

Against the background provided above, the primary contributions of this paper are as follows:

- We propose a novel method for ensuring driving safety and handling emergency situations of the AV with the aid of V2V and V2I communications, where the AV receives traffic information from the RBSs. Based on the proposed method, we formulate a deep autonomous vehicle optimization problem by jointly designing the speed and distance of the AV.
- We adopt a Linear Regression-based Speed evaluation and Jacobian Matrix-based Distance model for acquiring the trajectory of the AV. In the Jacobian Variant Linear Regression-based V2V communication model, the speed is first evaluated in the first hidden layer by means of linear regression function and distance is obtained in the second hidden layer via Jacobian Matrix. At each timeslot, based on the actual and estimated speed and distance, the recommendation is made for smooth V2V autonomous vehicle communication. On the other hand, Laplacian function is employed in the third hidden layer for robust V2I recommendation.
- We conceive a Deep Regression and Euler Recommendation enabled autonomous vehicle communication-based algorithm in the fourth hidden layer for preventing the collision by applying Euler function in case of emergency situation.
- We demonstrate that the proposed Deep Jacobian Regression and Tate Bryant Euler Recommendation (DJR-TBER) based V2V and V2I autonomous vehicle communication outperforms the state-of-the-art method both in terms of its end-to-end delay and computational time. Additionally, the collision rate derived from the Deep Regression and Euler Recommendation algorithm assists is found to be reduced.

1.2. Organization of the paper

The rest of the paper is organized as follows. Section 2 reviews related works. In Section 3, the proposed Deep Jacobian Regression and Tate Bryant Euler Recommendation (DJR-TBER) based V2V and V2I autonomous vehicle communication conceived for solving the problem formulated are demonstrated. Experimental settings and numerical results are presented in Section 4, which is followed by conclusions in Section 5.

2. Related works

One of the predominant issues in Intelligent Transportation Systems (ITS) is road safety owing to the serious accidents not only results in high mortality but also causes infrastructure destruction. Therefore, significant safety measures have become possible owing to the tremendous evolution pertaining to information and communications technologies. Accordingly, one of the solutions towards safe and secure driving is by means of autonomous vehicles.

In [7], a Visible Light Communication (VLC)-based collision avoidance mechanism was designed with the objective of managing and supervising AVs that has high efficiency in vehicular environments. Here, roadside units (RSUs) were positioned at the roundabout entrances for efficient coordination between vehicles in V2I mode. With this type of synchronization pattern, vehicles were found to cross the roundabout in a simultaneous pattern with concurrency nature.

Deep learning techniques were applied in [8] with which the current trends in AV and future prospective were also analysed in detail. Yet another prediction and search framework was proposed in [9]. In prediction phase, spatio-temporal dynamics were analysed whereas in case of search phase, a tree-based algorithm was utilized therefore ensuring both efficiency and effectiveness.

Over the last decagon, one of the emerging technologies that have been swiftly developed is automation in road vehicles. Numerous interdisciplinary issues have been posed on the prevailing transportation infrastructure by autonomous vehicles (AV).

A Scalable Link Optimization (SSLO) algorithm was proposed in [10] by deploying smart city use case with stable and reliable connectivity. However, latency factor was not focused. To address on this aspect, a handover operation via fast inter-operator was designed in [11] on the basis of using pre-registration on multiple operators. This in turn minimized the handover time in turn ensuring maximum E2E latency considerably.

Modern autonomous vehicles are frequently instrumented using radars diversified weather perception types. Despite, the functionality of radar is said to be constrained in acquiring the reflector positions in the environment. In [12], the feasibility of smart transportation was proposed with the objective of providing robust information to automotive radars. For this purpose, a spatial encoding scheme was introduced on the basis of geometrical layout. However, safety aspect was not focused. To concentrate on this issue, a LiFi based security framework was designed in [13]. However, the absence of connectivity of an AV with its neighbouring vehicles and infrastructure results in huge crashes. The challenges involved in the absence of connectivity were elaborated in [14].

To mitigate congestion and manage vehicles in computationally efficient manner, traffic light-free intersection control is employed. With the aid of V2V and V2I, vehicles are permitted to cross the intersection ensuring both safety and efficiency in traffic in the absence of traffic lights. But channel conditions with unstable nature however would result in the minimizing or compromise of travelling safety. In [15], an Autonomous Intersection Control (AIC) method was proposed by utilizing global optimization scheduling. With this type of scheduling, AV was prevented from collision and also attained robust traffic efficiency.

A Bezier curve-based recursive algorithm was designed in [16] that with the aid of Bezier curve created routes for vehicles with which communication between On-Board Unit (OBU) and Road-Side Units (RSUs) were ensured. Moreover, very low overhead was also incurred due to the consideration of inflexion points. Yet another altruistic reward function was presented in [17] that in turn enabled AV to alter their velocities with the purpose of circumventing queuing during intersection between vehicles. Also, proximal policy optimization (PPO) algorithm was utilized for training the policy with the utilization of generalized advantage estimation (GAE) for estimating the corresponding state values. As a result, better traffic efficiency was ensured.

Space and velocity changes were obtained on the basis of motion behaviour of two vehicles. With these two types of changes, traffic characteristics were recorded by means of Navier-Stokes [18] equation. As a result, accuracy was ensured in V2V. Smart city under IoT was analysed in [19] by employing multi-objective optimization. With this low latency was ensured. Yet another method to improve detection accuracy using Gaussian-based measurement matrix was proposed in [20] to ensure high throughput and low error.

In summary, the speed and distance are the key technical aspect to be contemplated in the construction of autonomous vehicle using LiFi communication. There are numerous studies on the application of these two core aspects to the construction of smart cities. Although the speed and distance are extensively utilized in the construction of autonomous vehicle model, their specific applications in smart cities using LiFi are not clear. Therefore, an autonomous vehicle V2V and V2I recommendation method called, Deep Jacobian Regression and Tate Bryant Euler Recommendation (DJR-TBER) is analysed in this study, which is of great significance to smooth communication.

3. Methodology

An autonomous vehicle can perform functions by sensing the environment without the need for human intervention. Several sensors or IoT devices are included with vehicles to provide automatic driving capability and make robust autonomous vehicle recommendations. In this work, Deep Jacobian Regression and Tate Bryant Euler Recommendation (DJR-TBER) based V2V and V2I autonomous vehicle communication is proposed to ensure safety and provide mechanisms during emergency by means of Artificial Intelligence model. Figure 1 shows the structure of DJR-TBER method.

As shown in the above figure, in LiFi technology, the vehicle's head and tail lights are fitted with a sensor that modulates light for data transmission. On the other hand, data are received by photoreceptors installed on other vehicles or infrastructure systems. This in turn assists in forming a network of vehicles and infrastructures that ceaselessly communicate with each other without data loss or delay by ensuring data transmission via visible light. Also as illustrated in the above figure, LiFi utilization with autonomous vehicle can be performed in two different processes, Vehicle to Vehicle (V2V) communication and Vehicle to Infrastructure (V2I) communication.

The detailed description of the proposed Deep Jacobian Regression and Tate Bryant Euler Recommendation (DJR-TBER) based V2V and V2I autonomous vehicle recommendation in addition to handling in case of emergency situations followed by a system model are described below.

3.1. System model

In this section a system model for autonomous vehicle V2V and V2I communication is designed. The system model proposed in our work includes four entities namely, Roadside Base Stations (RBSs) "*RBSs*", Autonomous Vehicles (AVs) "$AV = \{AV_1, AV_2, \ldots, AV_n\}$", On Board Units (OBUs) "*OBUs*" and Road Size Units (RSUs) "*RSUs*", respectively. With the aid of these four entities, traffic lights by means of Light Fidelity (LiFi) transmit information between V2V and V2I. Figure 2 shows the proposed work system model. The "*OBUs*" in our proposed work are positioned in the "*AVs*" that acquires traffic information "(x, y, z, r)" from "*RBSs*" and immediately communicate, speed, braking

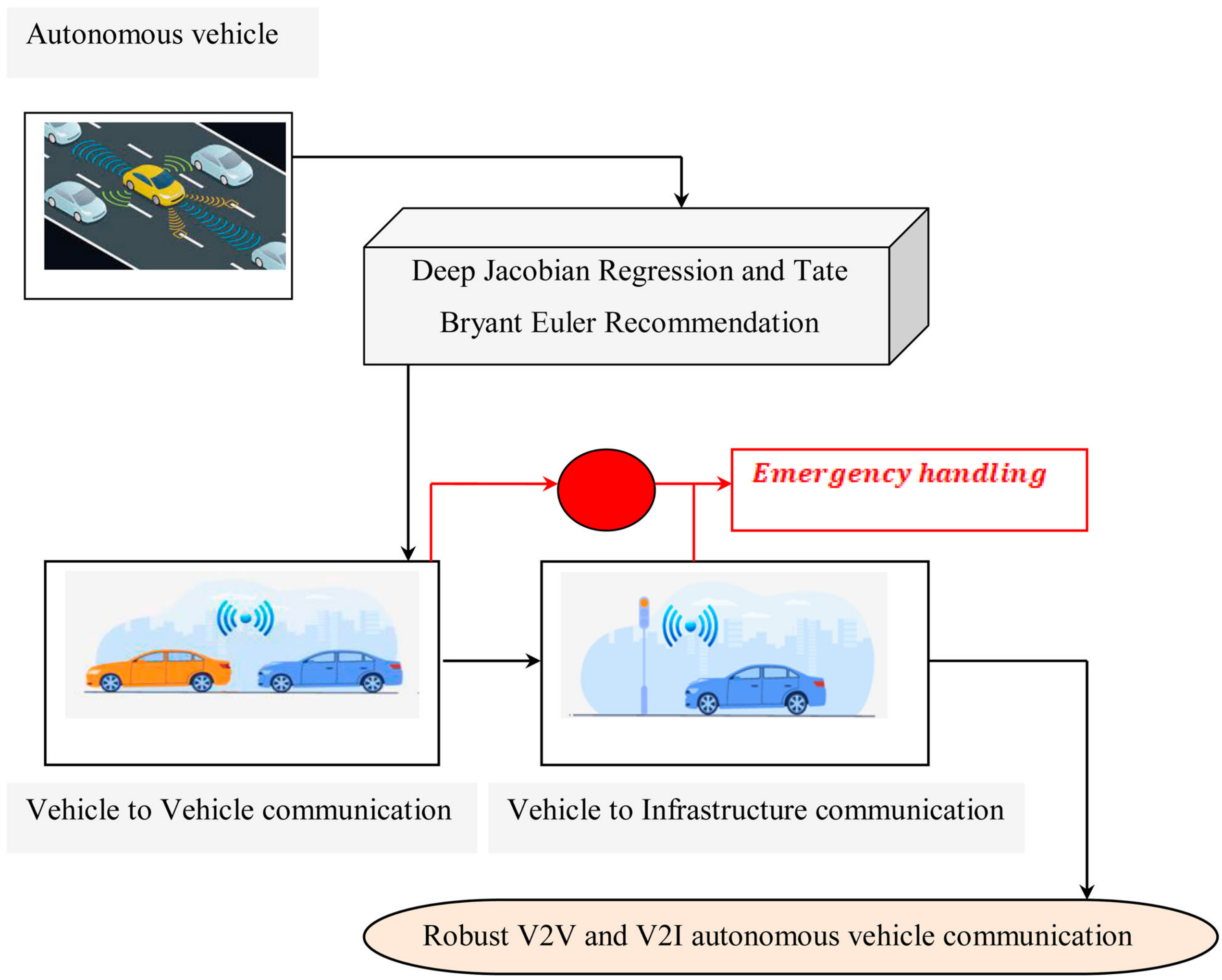

Figure 1. Structure of DJR-TBER method.

distance, driving directions and other vehicular information. On the other hand, the "*RSUs*" are requested for obtaining traffic information. Meantime, the traffic information is sent by the "*RSUs*" to "*RBSs*" via Internet. Such traffic information is proposed to be transmitted with the aid of LiFi by gaining advantage of light infrastructure previously positioned in vehicles. We focus for plotting the trajectory of the "*AV*" by jointly considering the driving safety and recommendations in case of emergency during V2V and V2I communication. This is owing to the reason that in terms of safety, collisions have to be avoided. Finally, recommendation in case of emergency is also designed.

The proposed Deep Jacobian Regression and Tate Bryant Euler Recommendation (DJR-TBER) based V2V and V2I autonomous vehicle communication is designed as given below. As shown in Figure 3, to start with the autonomous vehicle inputs are obtained via sensors (i.e. from ONCE dataset) in the input layer. First, V2V autonomous vehicle communication is performed via first and second hidden layer by means of Jacobian-variant Linear Regression model. Second, V2I autonomous infrastructure communication is done in the third hidden layer using Laplacian Scattered Vehicle to Infrastructure model. Third, emergency situation handling is performed via Tate-Bryant Euler Angle-based Emergency Handling model. Finally, safe V2V and V2I autonomous vehicle recommendation is made in a computationally efficient manner. A detailed description of the DJR-TBER method is provided in the following sections.

3.2. Deep Jacobian Regression and Tate Bryant EULER recommendation (DJR-TBER) method

As far as V2V communication, data transmission between vehicles or autonomous vehicles are said to take place via the front and rear lights. Information like the speed of the vehicle, braking distance, are said to be forwarded on to the tailing vehicles or other vehicles in the locality or neighbourhood area. This in turn assists in increasing the situational realization of autonomous vehicles and hence utilized in maintaining adequate distance between vehicles. Hence, with the enhancement of communication between vehicles, with no delay in data transmission, accidents are said to be minimized.

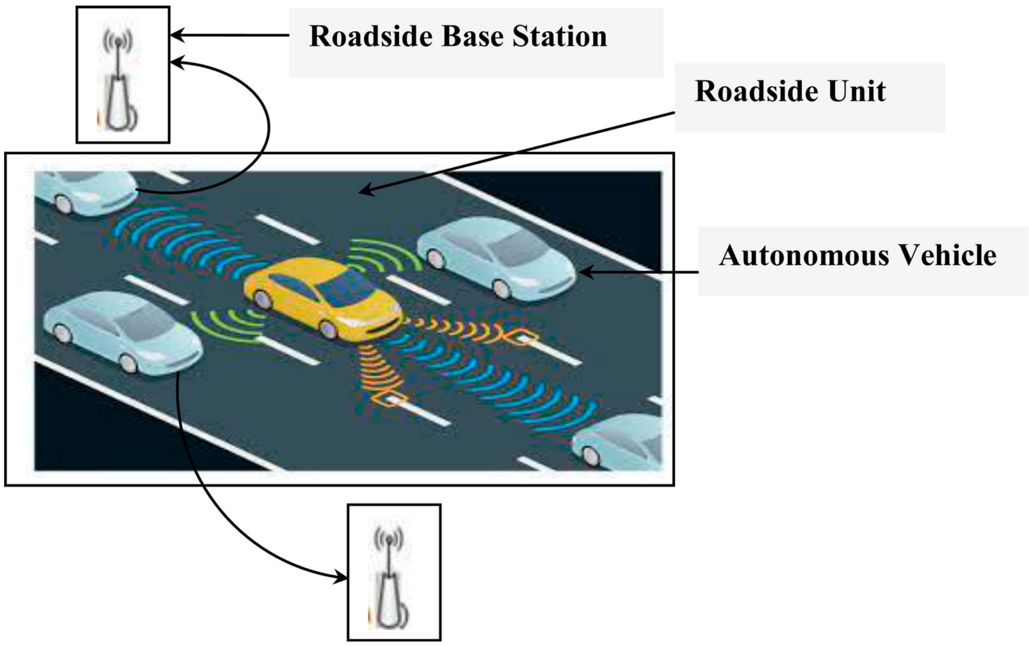

Figure 2. Proposed system model.

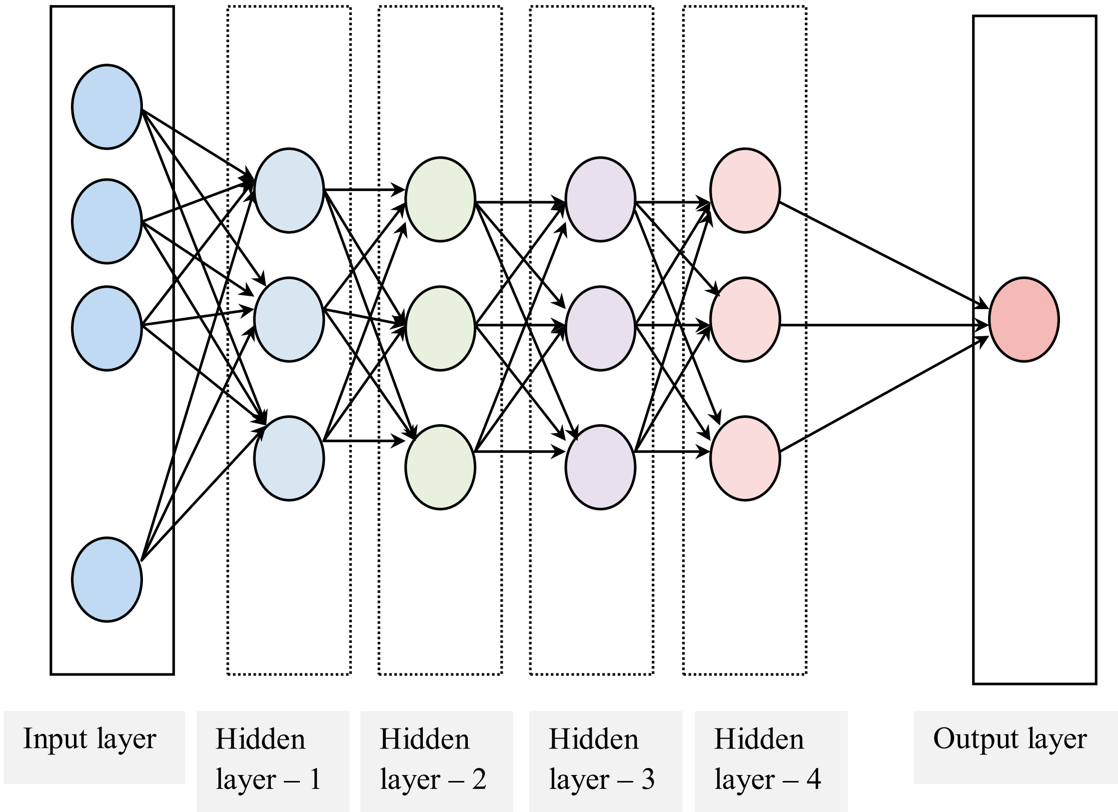

Figure 3. Deep Jacobian Regression and Tate-Bryant-Euler Recommendation method.

In this work, to achieve the objective of minimizing end-to-end delay and collision rate, a method called, Deep Jacobian Regression and Tate Bryant Euler Recommendation (DJR-TBER) is proposed. With the input vehicle information obtained from the input layer, in order to ensure safety and ensure mechanism in case of emergency situation each autonomous vehicle, "AV" in our work calculate its own speed "$S = V_1(S), V_2(S), \ldots, V_n(S)$" (i.e. "$V_i$"), vehicle braking distance "$D = V_1(D), V_2(D), \ldots, V_n(D)$" and also speed of neighbouring autonomous vehicle (i.e. "V_{i-1}"), respectively. This is acquired via the coordinates "(x, y, z)" and the infrastructure information by means of the reflection points "r" from the ONCE dataset. This action is performed in the first hidden layer by utilizing Linear Regression-based Speed evaluation model. The speed update at each "V" is modelled as given below.

$$S_i(t) = RC[V_{i-1}(S(t)) - V_i(S(t))] \quad (1)$$

From the above Equation (1), the speed "S" at time instance "t" is estimated based on the reaction criterion "$RC = \{0, 1\}$, *if* $RC = 0 \to V2V$ *communication*; *if* $RC = 1 \to V2I$ *communication*", current vehicle speed "$V_i(S(t))$" and the neighbouring vehicle speed "$V_{i-1}(S(t))$", respectively. Therefore, each vehicle utilizes the information obtained from its own sensors "$V[Sen_i]$", radar "$V[Rad_i]$", timely reports from the neighbouring vehicles "$V_{i-1}[t]$" for V2V communication and the closest "RSU" for V2I communication, respectively.

Moreover, data transmission between vehicles is said to take place via Front light "$FL = V_1(FL), V_2(FL), \ldots, V_n(FL)$" and Rear light "$RL = V_1(RL), V_2(RL), \ldots, V_n(RL)$" of each vehicle. Finally, the relationship between actual speed "$V_i(AS)$" and the measured speed via a linear regression function "$Lin_i(t)$" is formulated as given below.

$$Lin_i(t) = JM_i V[S_{i-1}(t)] + V[\varepsilon_i(t)] \quad (2)$$

From the above Equation (2), the linear function "$Lin_i(t)$" is formulated by means of a jacobian matrix "JM_i" for each vehicle "V", based on "$Lin_i \approx [V[Sen_i], V[Rad_i], V_{i-1}[t], RSU]$". In the second hidden layer, with the speed evaluation performed via linear regression function "JM_i" for each vehicle "V", the vehicle braking distance "$Dis_i(t)$" at time "t" Jacobian Matrix-based Distance model is evaluated for smooth communication between V2V in autonomous vehicle.

$$JM_i^T Lin_i(t) = JM_i^T JM_i Dis_i(t) + JM_i^T \varepsilon_i(t) \quad (3)$$

From the above Equation (3) by multiplying both the left hand and right hand sides by inverse of Jacobian matrix "$(JM)^{-1}$", the above equation is re-written as given below.

$$(JM)^{-1}[JM_i^T Lin_i(t)] = (JM)^{-1}[JM_i^T JM_i Dis_i(t)] + (JM)^{-1}[JM_i^T \varepsilon_i(t)] \quad (4)$$

Finally, the measured vehicle braking distance between autonomous vehicles at time "t" for V2V communication is obtained as given below.

$$Dis_i(t) = -(JM)^{-1}[JM_i^T \varepsilon_i(t)] \quad (5)$$

With the above resultant distance estimated, the conditions are checked with respect to actual vehicle braking distance. According to the results, Autonomous Vehicle LiFi Communication is recommended. On the contrary, the process is continued with other vehicles. The utilization of LiFi for smart traffic control for V2I communication necessitates bidirectional communication between vehicles and road entities or infrastructure. The infrastructure here includes road pavement, traffic lights, street lights, signages and so on. Moreover, V2I communication with Lifi also helps in enhancing road safety by ensuring quick data transmission.

Also due to the presence of large number of trees, road pavement, street lights and signages that cause scattering during wireless propagation. Hence, to ensure safe V2I communication, the path loss and path gain via Laplacian Scattered Vehicle to Infrastructure (V2I) communication are in the third hidden layer. The Laplace function here represents the linear mapping between the autonomous vehicles and hence ensuring smooth V2I communication. First, the path gain is obtained for the measured distance by employing Laplacian function.

$$PG[Dis_i(t)] = \frac{1}{FP}\left[\sum_{i=1}^{FP} |H\{Dis_i(t), FS\}|\right] \quad (6)$$

From the above Equation (6), the path gain "PG" with the distance between the vehicles "Dis" at time "t" is measured on the basis of the initialized frequency points "FP" and the frequency sample "FS", respectively. Followed by which the path loss is estimated as given below.

$$PL[Dis_i(t)] = log_{10}\frac{Dis_i(t)}{Dis_{ref}(t)} \quad (7)$$

From the above Equation (7), the path loss "PL" is measured on the basis of the initialized reference distance "$Dis_{ref}(t)$". By means of estimating the path loss and path gain for each vehicle in line with communication, scattering due to wireless propagation are said to be reduced to a greater extent. With this, safe V2I recommendation is made. Finally, to handle emergency situation, a Tate-Bryant Euler Angle-based Emergency Handling model is designed in the hidden layer 4.

Suppose a vehicle Front Light "$V_i(FL)$" is driving on the target lane with a constant speed "S". In other words, the lateral distance during driving is assumed to be "0". The vehicle Rear Light "$V_i(RL)$" senses the infrastructure at time "t" with "$\gamma(t)$" denoting the angle between "$V_i(RL)$" and the longitudinal direction at time "t". Then, Tate-Bryant Euler angular velocity for each infrastructure via the reflections "r" is formulated as given below.

$$\Theta = \begin{pmatrix} Inf_1 \\ Inf_2 \\ Inf_3 \\ \ldots \\ Inf_n \end{pmatrix} \quad (8)$$

With the above angular velocity for each infrastructure "Inf", the lateral and longitudinal distance is mathematically stated as given below to recommend in case of emergency.

$$\tan[\gamma(t)] = \Theta\left[\frac{\partial_{yRL}(t)}{\partial_{xRL}(t)}\right] = \Theta\left[\frac{S_{yRL}(t)}{S_{xRL}(t)}\right] \quad (9)$$

From the above Equation (9), "∂_{yRL}" and "∂_{xRL}" denotes the lateral and longitudinal distance of each vehicle Rear Light "$V_i(RL)$", "S_{yRL}" and "S_{xRL}" denotes the lateral and longitudinal speed of each vehicle Rear Light "$V_i(RL)$", respectively. Let us further assume that "$P(V_i)$" is the place of vehicle Rear Light "$V_i(RL)$" and "AZ" the momentous accident locality with respect to infrastructure (i.e. being acquired via sensors). Moreover, let "$t(AZ)$" represent the time taken for vehicle Rear Light "$V_i(RL)$" to travel from starting position to "AZ", then to avoid accident or handle emergency situation is formulated as given below.

$$x_{FL}(t) < x_{RL}(t) - L_{RL}cos[\gamma(t)] \quad (10)$$

From the above Equation (10), "L_{RL}" denotes the length of the rear light of vehicle, and "$x_{FL}(t)$" denotes the longitudinal direction of vehicle. With the above obtained resultant values, scenarios involving emergency can be handled in an efficient manner. The pseudo-code representation of Deep Regression and Euler Recommendation enabled autonomous vehicle LiFi communication sustained IoT is given below.

As given in the above Deep Regression and Euler Recommendation enabled autonomous vehicle communication with the objective of ensuring safe communication between V2V and V2I, an artificial intelligence-based method is designed. With the autonomous vehicles obtained from the ONCE dataset, in the first hidden layer, speed is measured by measuring the relationship between actual speed and the measured speed via a linear function. Next, upon satisfaction of the condition, The first hidden layer's output is used as input to the second hidden layer.

In the second hidden layer, the distance is measured by means of Jacobian Matrix. Only upon satisfaction of the condition in the second hidden layer, autonomous V2V is recommended. In the third hidden layer, based on successful V2V recommended, path loss and path gain are measured to ensure V2I communication. Next, in the fourth hidden layer, emergency situations are handled Tate-Bryant Euler angular velocity for each infrastructure. Finally, the recommendations are provided as output in the output layer.

4. Experimental setup

In this section the proposed Deep Jacobian Regression and Tate Bryant Euler Recommendation (DJR-TBER) method are evaluated and compared its performance with respect to the state-of-the-art methods, Scheduling Scheme for Autonomous Vehicle [1] and New Deep Reinforcement Learning (NDRL) [2], respectively. The proposed algorithm is simulated in Python. First, the dataset description is provided, followed by which, performance analysis is made on the basis of end-to-end delay, collision rate and accuracy using table values and graphical representation.

4.1. ONCE dataset description

The ONCE dataset consists of 7 million corresponding camera images and 1 million LiDAR scenes. The information from the ONCE dataset is gathered from 144 h of driving and spans a variety of locations, times and weather conditions. A single 40-beam LiDAR sensor and seven high-resolution cameras mounted on a car are used to construct the data acquisition system. The ONCE dataset contains three different types of coordinate systems: LiDAR coordinates, camera coordinates and image coordinates. On the one hand, the centre of the LiDAR sensor is where the coordinates are located, with the x-axis pointing left, the y-axis pointing backwards and the z-axis pointing upward. The camera coordinates, on the other hand, are situated at the centre of the lens, respectively.

Finally, The image coordinate guarantees a 2D coordinate system, with the x-axis and y-axis running along the width and height of the image, respectively, and the origin present at the top-left of the image. Ten frames per second are used to record the LiDAR data. (FPS). Based on the LiDAR coordinate, the 3D coordinates (x, y and z) are created, with r standing for the intensity of the reflection. Each scene's point clouds are stored in a separate binary file, from which the 3D coordinates are used to estimate speed, distance and reflection intensity in order to gather information about the infrastructure.

4.2. Performance analysis of end-to-end delay

In this section, end-to-end delay is discussed to estimate the performance of the proposed method. While making recommendations to ensure autonomous V2V or V2I communication, a significant amount of delay is said to take place. It is defined as the time taken for an autonomous vehicle to reach the destination end. The overall end-to-end delay is mathematically formulated as given below.

$$Delay_{EE} = [t_{act}] - [t_{ex}] \quad (11)$$

From the above Equation (11), the end-to-end delay "$Delay_{EE}$" is measured by taking into evaluation, the actual arrival time "$[t_{act}]$" and the expected arrival time "$[t_{ex}]$", respectively. It is measured in terms of milliseconds (ms). Table 1 lists the end-to-end delay observed by substituting the values in Equation (11) using the proposed DJR-TBER and two existing methods, Scheduling Scheme for Autonomous Vehicle [1] and NDRL [2], respectively.

Algorithm Deep Regression and Euler Recommendation enabled autonomous vehicle communication

Input: Dataset "DS", Autonomous vehicles "$V = V_1, V_2, \ldots, V_n$", time "$t$", actual speed "$V_i(AS)$", actual vehicle braking distance "$V_i[Dis_i(t)]$", "$FL = V_1(FL), V_2(FL), \ldots, V_n(FL)$", Rear light "$RL = V_1(RL), V_2(RL), \ldots, V_n(RL)$"
Output: Collision minimized, safe and accurate V2V and V2I recommendation
Step 1: Initialize current vehicle speed "$V_i(S(t))$", neighbouring vehicle speed "$V_{i-1}(S(t))$", actual speed "$V_i(AS)$", Initialize frequency points "$FP = 25$", reference distance "$Dis_{ref}(t) = 5\,\mathrm{m}$", boundary limit "$BL = 500 * 500\,\mathrm{m}^2$", reference distance "$Dis_{ref}(t) = 5\,\mathrm{m}$", boundary limit "$BL = 500 * 500\,\mathrm{m}^2$"
Step 2: Begin
Step 3: **For** each dataset "DS" with vehicles "V"

//input layer
Step 4: Obtain (x, y, z, r) coordinates
Step 5: **End for**

//hidden layer 1 – speed evaluation
Step 6: **For** each dataset "DS" with vehicles "V"
Step 7: Estimate speed as in Equation (1)
Step 8: Measure relationship between actual speed and measured speed as in Equation (2)
Step 9: **If** actual speed "$V_i(AS) < Lin_i(t)$"
Step 10: **Then** Proceed to hidden layer2
Step 11: **End if**
Step 12: **If** actual speed "$V_i(AS) > Lin_i(t)$"
Step 13: **Then** abnormality observed in speed
Step 14: Update measured speed
Step 15: **Go to** step 6
Step 16: **End if**
Step 17: **End for**

//hidden layer 2 – distance evaluation
Step 18: **For e**ach vehicles "V" with established V2V communication
Step 19: Measure distance via Jacobian matrix as in Equations (3), (4) and (5)
Step 20: **If** actual vehicle braking distance "$V_i[Dis_i(t)] < [Dis_i(t)]$"
Step 21: **Then** V2V communication is normal
Step 22: Establish V2V communication
Step 23: **End if**
Step 24: **If** actual vehicle braking distance "$V_i[Dis_i(t)] > [Dis_i(t)]$"
Step 25: **Then** abnormality observed in distance between vehicles
Step 26: Update measured distance
Step 27: **Go to** step 18
Step 28: **End if**
Step 29: **End for**

//hidden layer 3 (V2I)
Step 30: **For** each vehicles "V" with established V2V communication and measured distance "$Dis_i(t)$" between autonomous vehicles
Step 31: Estimate the path gain as in Equation (6)
Step 32: Estimate the pass loss as in Equation (7)
Step 33: **If "**$PG[Dis_i(t)]\&\&PL[Dis_i(t)] < BL$"
Step 34: **Then** recommend V2I communication
Step 35: Else
Step 36: Do not recommend V2I communication
Step 37: **End if**
Step 38: **End for**

//hidden layer 4 – attend emergency
Step 39: **For** each vehicles "V" with established V2I and V2I communication
Step 40: Evaluate Tate-Bryant Euler angular velocity for each infrastructure as in Equation (8)
Step 41: Measure lateral and longitudinal distance as in Equation (9)
Step 42: **If "**$t > t(AZ)$"
Step 43: **Then** no collision
Step 44: **End if**
Step 45: **If "**$t < t(AZ)$"
Step 46: **Then** possibility of collision
Step 47: **Go to** step 39
Step 48: **End if**
Step 49: **End for**

//output layer
Step 50: **For** each vehicles "V" with established V2I and V2I communication
Step 51: Smooth and robust V2V and V2I recommendation
Step 52: Accident prone V2V and V2I recommendation
Step 53: **End for**
Step 54: **End**

Figure 4 illustrates the graphical representation of end-to-end delay analysis with respect to 5000 vehicles involved in the simulation process performed under diversified environments. From the above figure, a linear increase is found in the end-to-end delay using all three methods. In other words, an increase in the number of vehicles causes an increase in the network traffic and with this, the end-to-end delay or the time consumed in propagating vehicles between ends increases, therefore resulting in the increase in the end-to-end

Table 1. End-to-end delay evaluation using DJR-TBER, Scheduling Scheme for Autonomous Vehicle and NDRL.

	End-to-end delay (ms)		
Vehicles	DJR-TBER	Scheduling Scheme for Autonomous Vehicle	NDRL
500	175	275	375
1000	215	315	435
1500	285	385	485
2000	335	445	555
2500	350	490	615
3000	425	550	685
3500	485	585	745
4000	545	655	835
4500	620	735	885
5000	635	790	900

Table 2. Collision rate evaluation using DJR-TBER, Scheduling Scheme for Autonomous Vehicle and NDRL.

	Collision rate (%)		
Vehicles	DJR-TBER	Scheduling Scheme for Autonomous Vehicle	NDRL
500	9	14	19
1000	10.25	15.25	20.45
1500	11	16.35	23.25
2000	12.45	17.25	24.25
2500	13.35	19.55	26.15
3000	15.15	21.35	28.35
3500	18.25	24.55	30.25
4000	21.35	28.25	34.15
4500	25.45	31.45	36.35
5000	28.25	36	39.45

delay. However, simulations performed for 500 vehicles using the proposed DJR-TBER method observed 175, 275 ms using [1] and 375 ms using [2], respectively. From this, the end-to-end delay with the proposed DJR-TBER method was found to be comparatively lesser than [1] and [2]. The reason behind the minimization of end-to-end delay using DJR-TBER method was due to the application of Linear Regression-based Speed Evaluation model in the first hidden layer that measures the relationship between actual speed and measured speed using linear regression function. On the basis of the results further proceedings are made. With this, the actual arrival time was less due to the consideration of timely reports from neighbouring vehicles that in turn reduced the end-to-end delay using DJR-TBER method by 24% compared to [1] and 39% compared to [2].

4.3. Performance analysis of collision rate

This section discusses the relative effectiveness of various collision accident prevention (i.e. emergency situation management) strategies in contexts that are similar. The situation where various methods can ensure safety under various initial circumstances is thoroughly examined. The ratio of accidents to all simulations is known as the collision rate.

$$CR = \sum_{i=1}^{n} \frac{V_{Collision}}{V_i} * 100 \qquad (12)$$

From the above Equation (12), the collision rate "CR" is measured based on the total number of simulations made with autonomous vehicles "V_i" and the actual autonomous vehicles met with collision "$V_{Collision}$". It is measured in terms of percentage (%). Table 2 lists the collision rate obtained by substituting the values in Equation (12) using the proposed DJR-TBER and two existing methods, Scheduling Scheme for Autonomous Vehicle [1] and NDRL [2], respectively.

Figure 5 illustrates the graphical representation of collision rate with different driving regions for an average of 144 driving hours. From the above figure, it is inferred that an increase in the number of vehicles acquired from LiDAR frames results in the number of increase in the frames and this in turn increases the collision rate also. However, with an average of 10

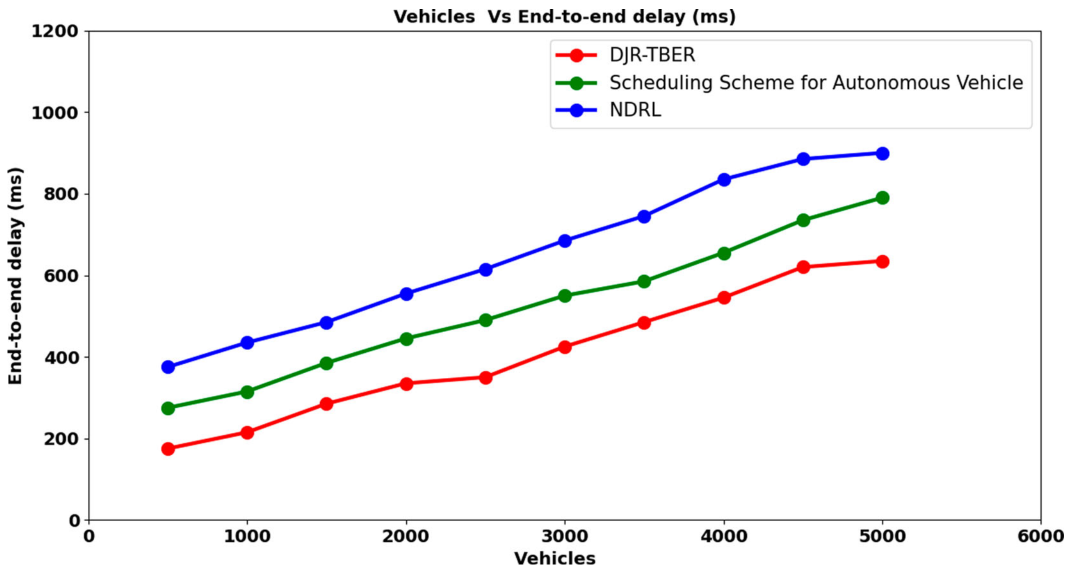

Figure 4. End-to-end delay analyses versus vehicles.

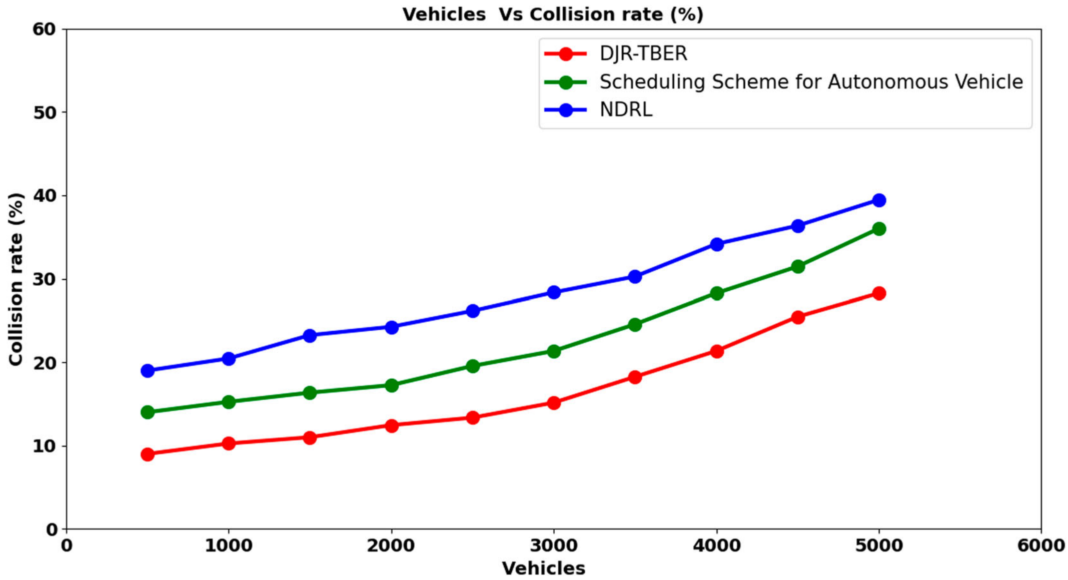

Figure 5. Collision rate analyses versus vehicles.

simulation runs performed using the three methods, DJR-TBER, Scheduling Scheme for Autonomous Vehicle and NDRL, the collision rate using DJR-TBER was found to be comparatively lesser than [1] and [2]. The reason behind the minimum collision rate using the proposed DJR-TBER method was due to the estimation of distance by employing Jacobian Matrix. With this, the targeted results were obtained (i.e. V2V communication in autonomous vehicle) with least possible function towards the best number of iterations. Also, to establish V2I communication, a separate Laplacian function was employed in the third layer based on the initialized frequency points and frequency sample, respectively. As a result, the collision rate using DJR-TBER method is said to be reduced by 28% compared to [1] and 43% compared to [2], respectively.

4.4. *Performance analysis of recommendation accuracy*

Recommendation accuracy estimates the rate of accuracy at which the actual recommendation has been made by a specific method. To be more specific, recommendation accuracy "R_{acc}" refers to the percentage ratio of V2V and V2I communications recommended correctly by the respective roadside base station "*RBS*" to the autonomous vehicles employed for simulation purpose "V_i". It is measured in terms of percentage (%). The recommendation accuracy is mathematically formulated as given below.

$$R_{acc} = \sum_{i=1}^{n} \frac{V_{CR}}{V_i} * 100 \tag{13}$$

Finally, Table 3 provides the recommendation accuracy made by substituting the values in Equation (13) using the proposed DJR-TBER and two existing methods, Scheduling Scheme for Autonomous Vehicle [1] and NDRL [2], respectively.

Table 3. Recommendation accuracy evaluation using DJR-TBER, Scheduling Scheme for Autonomous Vehicle and NDRL.

	Recommendation accuracy (%)		
Vehicles	DJR-TBER	Scheduling Scheme for Autonomous Vehicle	NDRL
500	93	90	87
1000	92.25	83.25	80.25
1500	90	80.45	75.35
2000	88.15	76.35	72.15
2500	86.35	74	71.45
3000	82.25	70.25	67.25
3500	78	68.35	62.45
4000	75.15	65	60.35
4500	72	62.15	59.35
5000	70.15	60	58

Finally, Figure 6 shows the recommendation accuracy noticed for 5000 different vehicles acquired from fully annotated scenes with five classes in diverse environments. A decrease in the recommendation accuracy is observed with the increase in the number of vehicles involved for 10 different simulation runs. This is owing to the reason that the vehicle information is obtained from diverse environments ranging from day/night, sunny/rainy and urban/suburban areas. However, simulation performed with 500 vehicles showed an improvement of 93% using DJR-TBER method, 90% using [1] and 87% using [2]. These findings showed that the DJR-TBER method's recommendation accuracy was superior to that of [1] and [2]. The application of Tate-Bryant Euler angular velocity for each infrastructure via reflections that with the aid of lateral and longitudinal distance obtain accurate recommendation was the reason for the improvement. As a result, it was discovered that the DJR-TBER method's

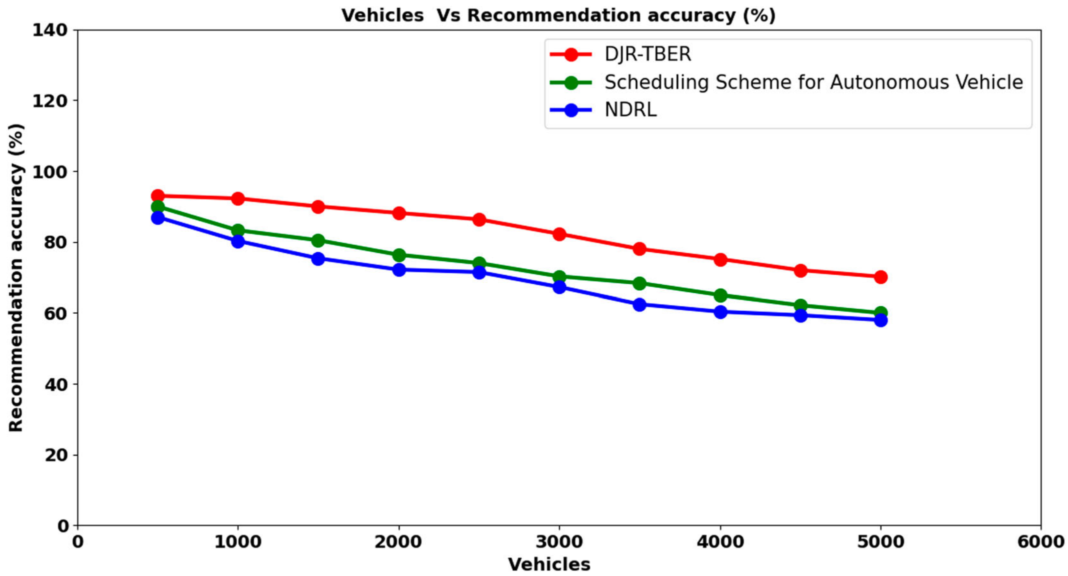

Figure 6. Recommendation accuracies versus vehicles.

recommendation accuracy was 20% and 14% better than that of [1] and [2], respectively.

5. Conclusion

The joint design of V2V and V2I autonomous communication, recommend in case of emergency situation was considered while enhancing driving safety. To tackle the problem formulated, a deep Tate-Bryant-Euler Recommendation based algorithm was proposed for determining the speed and distance of the AVs. By obtaining real-time traffic information from ONCE dataset, the AV was shown to recommend both V2V and V2I communication ensuring safe driving. It was also demonstrated that the proposed Deep Regression and Euler Recommendation enabled autonomous vehicle LiFi communication sustained IoT was capable of ensuring safety mechanism even in case of emergency. Extensive simulation results were provided to demonstrate that the proposal can enhance or boost the performance of autonomous vehicle braking in an emergency, thereby making certain V2V and V2I safety. The performance of the proposed method was analysed in terms of end-to-end delay, collision rate, recommendation accuracy and it was compared to the state-of-the-art methods. Numerical results showed that the proposed method outperforms the state-of-the-art methods and yields lower end-to-end delay and collision rate ensuring better recommendation accuracy for autonomous vehicle LiFi communication for sustained IoT.

6. Future scope

There are various possible avenues of inquiry for future research. First, additional research might concentrate on improving the technology to handle various emergency scenarios and adapt to growing traffic conditions. Incorporating real-world field tests and validations would also offer more thorough insights into the efficiency and efficacy of the system.

It would also be advantageous to investigate the proposed approach's scalability and robustness in larger-scale scenarios and complicated metropolitan contexts. Given the dynamic nature of communication technologies, it would also be beneficial to look at how to include new communication technologies, such as 5G or future wireless network generations, into the V2V and V2I architecture.

A new algorithm for V2V and V2I autonomous communication in emergency conditions was given in the paper, in conclusion, the study demonstrated a unique algorithm for autonomous V2V and V2I communication in emergency scenarios, demonstrating its efficiency in raising driving safety. The future of autonomous vehicles and IoT-enabled transportation systems looks bright given the suggested algorithm and the shown possibilities for LiFi connectivity.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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