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DIB - A Novel Optimized VANET Traffic Management Using a Deep Neural Network

P. Sankar[1], Dr. M. Robinson Joel[2], Dr. A. Jahir Husain[3]
[1]Research Scholar,
Department of Computer Applications,
PRIST University,
Vallam, Thanjavur, India
sankmca@gmail.com
[2]Associate Professor,
Department of Information Technology,
Kings Engineering College, Chennai, India
joelnazareth@gmail.com
[3]Assistant Professor,
Department of Computer Applications,
B.S.Abdur Rahman Crescent Institute of Science and Technology,
Vandalur, Chennai, India
jahirhusain@crescent.education

Abstract— The advancement of the Internet of Things (IoT) establishes the development of the Internet of Vehicles (IoV) and Intelligent Transportation Systems (ITS). An integral part of ITS is the vehicular ad hoc network (VANET) with smart vehicles (SV). In this research, a dynamic method of traffic regulation in VANET is presented using Deep Neural Networks (DNN) and Bat Algorithms (BA). With a reduced average delay, the former (DNN) is utilized to guide vehicles across very crowded routes to increase efficiency. In order to examine the traffic congestion status between network nodes, BA is integrated with the IoT and moved over VANETs. Experiments were conducted to test the effectiveness of the proposed method with various parameters such as average latency, packet delivery ratio (PDR) and throughput and the performance were compared with different machine learning (ML) algorithms. The simulation outputs proved that the proposed technique supports real-time traffic circumstances with less energy usage and delay than existing methods.

Keywords- Deep Neural Network, Intelligent Transport System, Internet of Things, Machine Learning, VANET.

I. INTRODUCTION

In recent years, research on vehicular ad hoc networks (VANETs) has gained importance for both academic and industrial researchers due to the development of wireless communication technology and the growth of the vehicle industry. Since it is anticipated that there will be more than 2 billion registered vehicles by the end of the next decade, VANETs will be essential to the global communication network [1]. VANETs can be thought of as a part of Intelligent Transportation Systems (ITS), since it enhances the effectiveness of the transportation system and ensure the safety of cars, passengers, and pedestrians.

Nowadays, vehicles are increasingly turning into intelligent terminals due to the advance of Internet of Things (IoT) and artificial intelligence [2] [3]. The essential component of an intelligent vehicle is an onboard device that functions as a minicomputer with a network connectivity [4] [5].

In the VANET, four different communication types have been identified: (i) vehicle-to-vehicle (V2V) communication; (ii) vehicle-to-road infrastructure communication (V2I); (iii) In-vehicle (InV) communication and (iv) vehicle-to-broadband cloud (V2B) communication [6].

Communication system installed inside a car is referred to as in-vehicle communication. It is crucial and essential for VANETs study since it can identify a driver's physical state, such as drowsiness or fatigue, which is harmful for the car, the driver and other road users.

V2V communication is the system that allows drivers to share alerts and information in order to assist one another in situations like traffic jams or accidents, among other things.

Drivers may monitor their environment and receive real-time updates on traffic and weather conditions enabled by the *V2I* communication system.

V2B communication is the system that allows for the interconnection of automobiles using wireless broadband technologies like 4G and 5G. The cloud-connected ITS will offer monitoring data, traffic data, and entertainment. This

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V2B technology can be used for assisting the driver and vehicle tracking.

Recently, VANETs have given their users the tools for managing their data and their safety, with the control techniques being created to function in any situation based on network dynamics [7]. Associated with the growing usage of automobiles in VANETs, traffic management is made more difficult by the employment of 'centralized and distributed' algorithms [7]. Moreover, the growth in traffic has an indirect impact on urban transportation, increasing travel times, fuel use, and pollution levels [8].

The performance of VANETs is greatly impacted by a number of issues, including poor connectivity, restricted scalability, less flexibility and insufficient intelligence. These issues also cause delays in time and channel congestion.

Due to the tremendous increase in traffic, the complexity of traffic management analysis increases [9]. So, for flexible and easier transmission for automobiles with diverse limitations such as exponential increase in traffic, limited computing resources and uncertainty, a high-end intelligent system is required. Deep learning methods are used in high-end systems to control network abstraction and resource optimization. Different security-based protocols [10, 11, 12] and machine learning methods [13, 14] are being developed by researchers for use in a variety of wireless communication and data prediction applications.

In order to achieve this goal, we present the Bat Algorithm (BA) [15] as a key component and to provide required data to help the DNN based routing algorithm to select the best choices.

Here, we have proposed a novel method called Deep Neural Network (DNN) with IoT-Based Bat Agents (DIB) with the following objectives:

- To use the DNN [15] method with BA to enhance the VANET routing.
- To analyze the DIB model with the existing DNN and ANN model with various parameters such as latency, packet delivery ratio, throughput and failure rate.

This paper is arranged in the following manner: Literature review is given in section 2; section 3 provides the proposed network model; In Section 4, the results of the proposed model are compared to the existing models. Section 5 is the conclusion section which summarizes and specifies the research directions we have planned to carry out in future.

II. LITERATURE REVIEW

ITS significantly encourages connection between the vehicles and the roadside units (RSU) within VANETs in order to provide effective and secure transmission. Other issues including limited scalability, flexibility, bad connectivity, and insufficient intelligence cause communication channel congestion and time delays, which have a big impact on the performance of VANET.

To address these difficulties in traffic management, numerous studies are conducted in the existing literature [16-18]. These techniques are used to address issues with scalability, performance, and management as well as traffic congestion in VANETs. In an urban environment, several optimization activities are carried out to guarantee the control of traffic flow dynamics [19].

By providing reliable information regarding road conditions, VANETs play a crucial role in autonomous vehicles. Additionally, VANETs offer a number of services, including error identification, secure transportation, scheduling of resources, limiting the energy usage, etc. [20].

The author of [21] proposed three ML methods for predicting short-term congestion using vehicle movement data from connected vehicles. Three kinds of prediction models suggested by the author: Offline models that use past data and real-time updates are used by online models.

In [22], the researchers make projections on the models of vehicle collecting and handling routes. This approach is built on a video collection device, an automatic process for extracting routes, and a post-processing algorithm designed explicitly for eliminating errors and establishing reliable speed and acceleration. Deep learning neural network is used in [23] to address numerous traffic-related problems based on GPS route data collected from running vehicles.

The authors of [24] describe an approach for grasping the environment based moving habit of vehicles and to obtain the path. In [25], the researchers provide analysis of data taken from the Mobile Century experiment. Pre-processed GPS trace data has been prepared as a result of the data that has been obtained and proposed.

III. PROPOSED SYSTEM

3.1. Network Model

The modern 5G enabled VANET model with SDN support is shown in figure 1. All the four types of communications are shown in this model. It contains the following entities to design the infrastructure:

Smart Vehicles (SVs):

SVs are the key entities of the ITS system. Each SVs are capable of communicating with each other by ad hoc mode and to the RSU.

Road Side Units (RSU):

RSUs are the communication points thru which the SVs can communicate to the road side infrastructure. These are the traffic control system units operate on the 5.9 GHz DSRC band for rapid communication. Moreover, RSUs are playing as the Certificate Issuing Authority in our proposed model. Every SV has to register with the RSU to get the

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authentication certificate. In other words, RSUs are the responsible entity to issue and revoke authentication certificate to SVs.

On-Board Unit (OBU):

The communication between various parts of a vehicle is made using different sensors by a device attached on a vehicle called as OBU. In addition OBU is also responsible for communication with RSU and other vehicles. An OBU can be considered as a mobile node in the VANET while the RSU is a fixed node.

5G network:

5G network can be seen as a key technology providing pervasive connectivity, low-latency and more reliable communication in VANET [26]. 5G uses a combined platform to provide the required services [27]. The spectrum assigned for 5G empowers modern connectivity with advanced spectral and power proficiency earned through the improvement of millimeter-wave [28] and massive multiple-input multiple-output (MIMO) arrays [29]. Further it is compatible with the existing and future communication methods hence, it can provide a variety of user friendly services.

City Traffic Control (CTC):

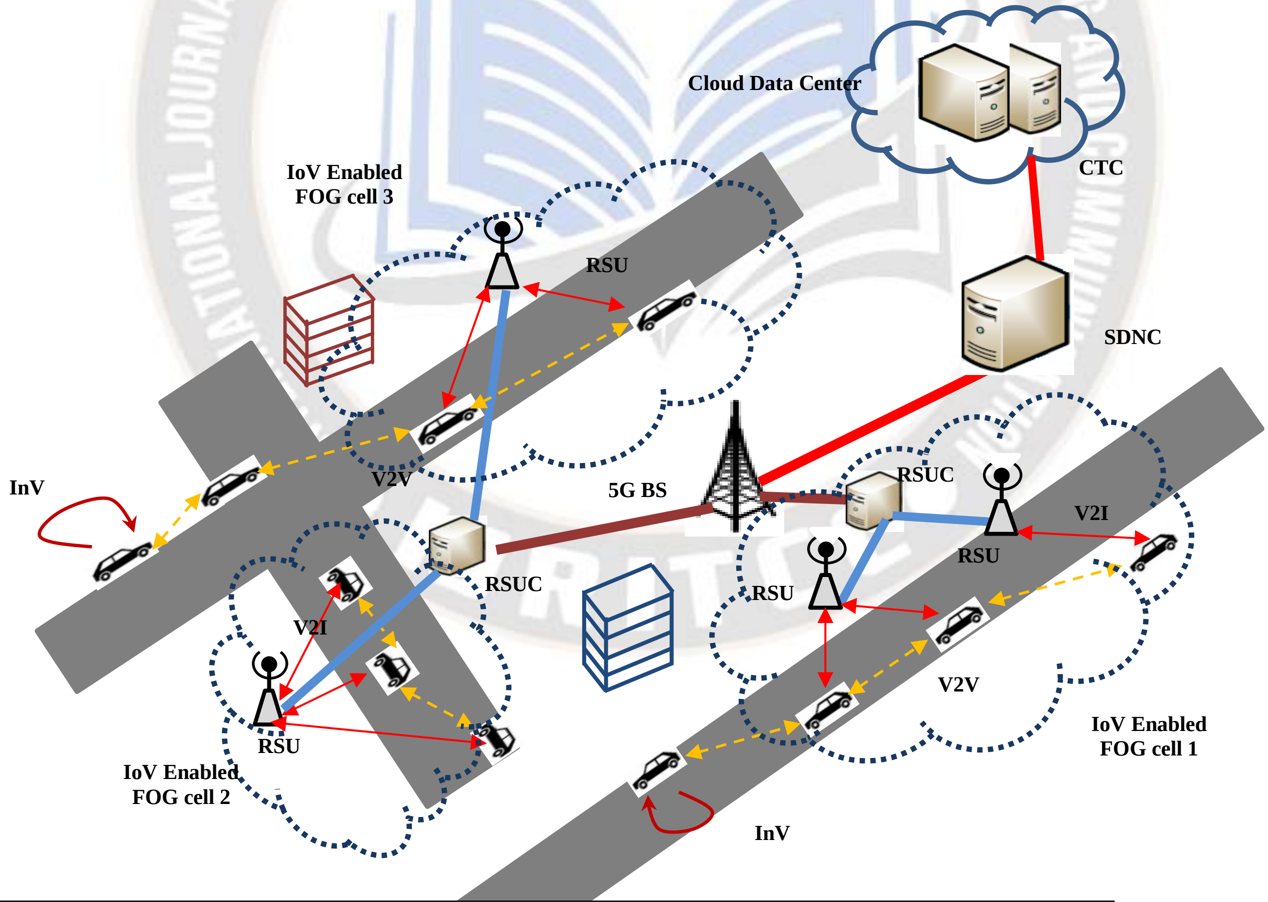
It is a cloud based server it controls the overall city traffic with the help of several zonal controls (ZCs) which in turn control the traffic through the 5G network.

Road Side Unit Controller (RSUC)

RSUC is the controlling station of all the RSUs where the communication between all the RSUs is taking place. RSUC is responsible for interconnecting all the RSUs and controlling their functions.

Software Defined Network Controller:

The SDN controller is responsible for the global policies, like authentication and traffic management. The suggested approach was tested in a city environment with grids and crossings of roadways. A collection of numerous parameters, such as width and length of roads, traffic density and the number of roads between two junctions are provided by the path between any two crossings [30, 31, 32].



SDNC – SDN Controller
5G BS – 5G Base Station
RSU – Road Side unit
RSUC- RSU Controller
CTC - City Traffic Control

Figure 1. 5G enabled VANET with SDN support

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Every SV has a special identifying number (ID) that includes the vehicle's position, direction, and speed. Vehicles automatically contacted the RSU to comprehend the total number of intersections, traffic segments, and levels of congestion.

In this research, IoT enabled Bat Algorithm is employed to deliver more accurate vehicle data than the present vehicle communication methods. By creating the graph G = <V, E>, the DNN made the correct destination in the suggested approach. In G, V represents the intersection points between the source and the destination of the vehicles and E represents te number of the road sections connected between the junctures in V.

3.2 Traffic Control System

The DIB traffic control model works as an automated system that utilizes IoT assisted BA (BATIoT) to gather traffic data of the nearer road segments and transmits the same to the RSU.

The distributed graph-based traffic management system has a set of vehicles (V) and edges (E). DIB transmits information on the vehicle density on the road and the level of traffic around the intersections. In the suggested approach, the functional module is assisted by the BAT algorithm, which subsequently communicates with the vehicle unit to perform routing activities. The work flow of functional module is depicted in figure 4.

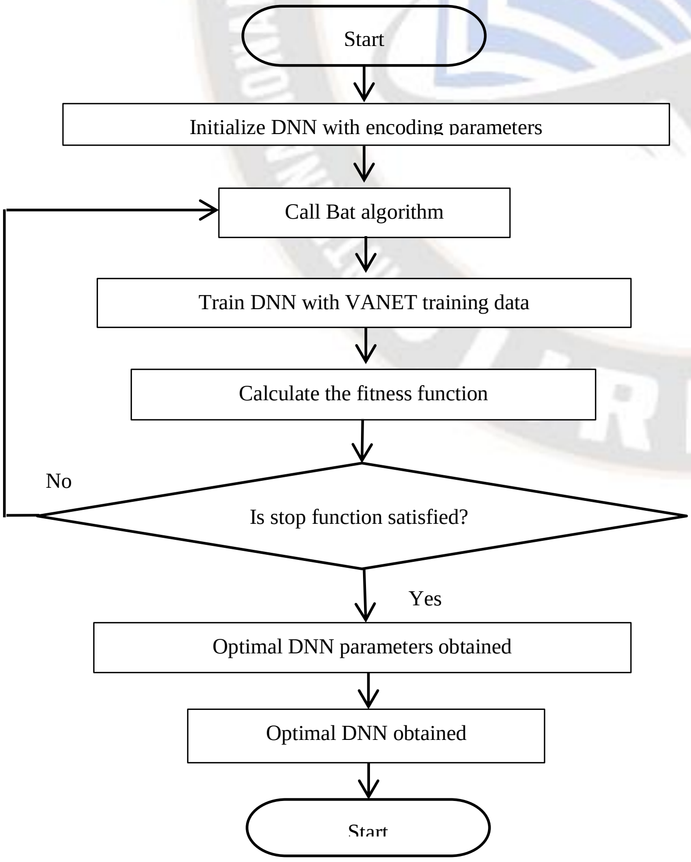

Figure 2. DNN Work flow chart

In the proposed system, the BATIoT is an active module that connects SVs with the functioning module. This module uploads SVs data onto the DNN to forward data packets from the source to the destination with the help of the cooperative bats via the selected rout.

Each BATIoT system has a distinct identity because they contain a variety of information. A road segment's current traffic statistics are kept in the cloud and the DNN, a key indication of packet transfer determines the routing path. At last, the data space entirely saves the information from the automobile units. At this time, the DNN routing path is located in the RSU [33].

3.3 Functioning Module

Functioning module performs a key role in finding out the route. This module calculates the route of the vehicle by considering the following parameters: Current position, destination, speed and the congestion in different road segments. DNN with optimized Bat algorithm is employed in this module. Figure 2 shows the workflow of this module and figure 3 shows the layers of DNN.

3.4 The BAT Algorithm

The way that bats use echolocation to measure distances is the source of inspiration for the BA. Bats often use short, loud sound impulses to detect obstacles or prey during the night when they are hunting. A bat's unique hearing system may be used to determine the object's size and location. Based on this aspect of bat echolocation, Yang [34] proposed the BA. The steps of BAT algorithm is described below:

The Bat algorithm mimics the echolocation technique used by bats to differentiate between physical objects and prey. In order to find prey, bats fly in a random motion with speed v_i at location x_i, with a recurrence of f_{min}, turbidity A_0, and shifting wavelength λ. These behaviors are examples of how bats distinguish differences.

The pulse discharge rate r [0, 1] varies depending on how well the fitness function is approximated by the recurrence that the bats naturally modify. The loudness typically ranges from a big A_0 (positive value) to a small A_{min} (constant value).

Our proposed approach includes the operation parameters such as frequency, position, velocity, emission pulse rate, and loudness. These concepts aid bats in their pursuit of prey in a D-dimensional environment. Following the arbitrary initiation, the next position and speed are recorded in a regular interval t, which is shown in equations (1) to (3), to achieve the Virtual Bat Movement.

$$f_i = f_{min} + (f_{max} - f_{min}) \text{ x } \beta \quad (1)$$

$$v_i^{t+1} = v_i^t + (x_i^t - x_*) \text{ x } f_i \quad (2)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (3)$$

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The best solution is picked for a local search, and the new solution is then locally created for each bat by using the criterion given in equation (4).

$$x_{new} = x_{old} + \varepsilon * A^t \quad (4)$$

where:

f_i is the frequency;
v_i^t is the velocity;
x_i^t is the position;
A_t is the loudness;
r_i^t is the emission pulse rate;
x_*_ is the global best;
f_{min} is the minimum frequency;
f_{max} is the maximum frequency.
ε is the arbitrary vector

When we have the better fitness function from N bats than the previous best f(x*), the global solution is updated.

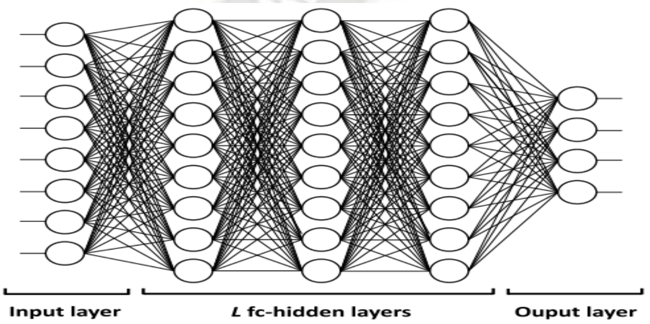

Figure 3. Layers of DNN

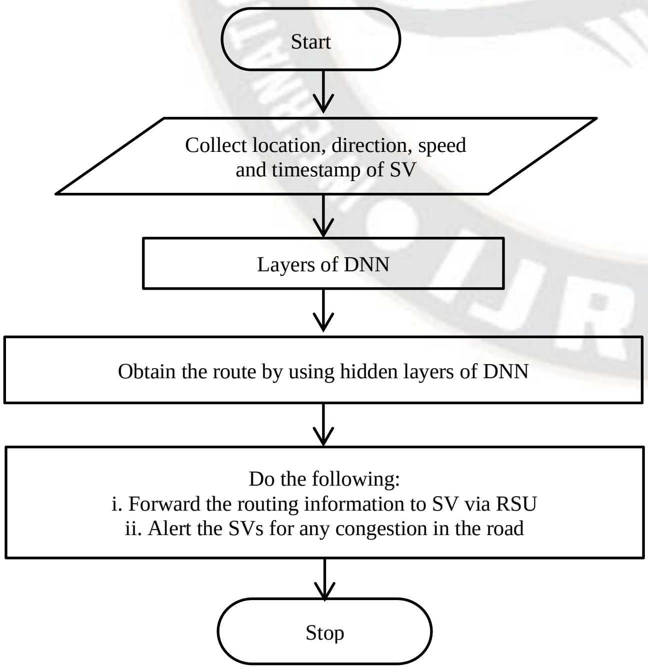

Figure 4. Work flow of functional module

IV. PERFORMANCE EVALUATION

The proposed approach is simulated by using a Python compiler. The simulation parameters are given in table 1. The experiment is conducted in a 1500 m^2 region on a dual way road with 300 vehicles, in an urban environment with the maximum speed 50 km/h. IEEE 802.11p MAC protocol was employed to calculate the packet interval and refresh the report on secured packet transmission. Retransmission of the failed packets during the broadcast is also done in this experiment.

Table I – Simulation Parameters

Sl.No	Parameters	Value
1	Total number of vehicles	100–300
2	Carrier frequency of the channel	5.9 GHz
3	Maximum transmission	20 mW
4	Area of simulation	1500 m^2
5	Velocity of the vehicles	50 km/h
6	Bit rate	18 Mbps
7	Transmission range	500 m
8	Beacon interval	0.5 s
9	MAC protocol	802.11 p
10	Simulation time	1000 s

The proposed technique is validated using two deep learning models that are already in use: DNN and Artificial Neural Network (ANN) [35] [65]. Without using BA's predictions or inputs, the DNN and ANN are trained directly using the proposed module. In order to evaluate the average latency and cumulative distribution function (CDF) we have used different performance criteria including network density, vehicle speed, and the types of transport.

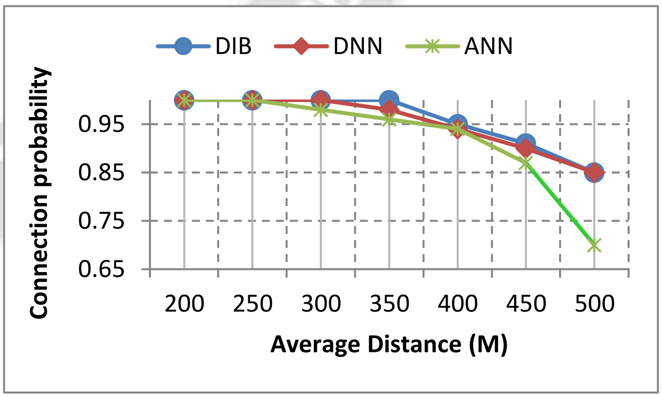

Figure 5.(a)

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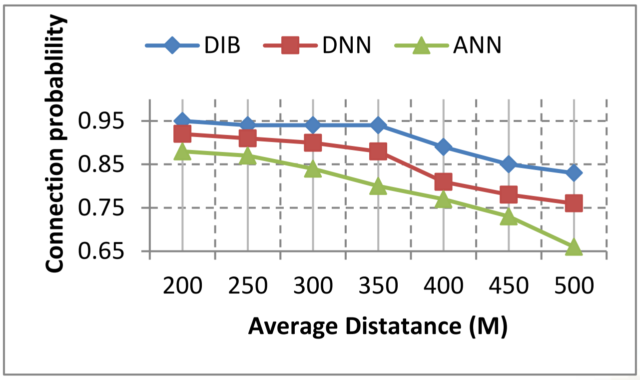

Figure 5.(b)

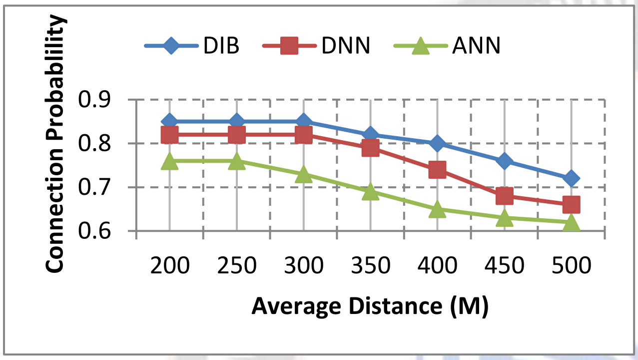

Figure 5.(c)

Figure 5.Connection probability vs Vehicle density (a) 30kmph (b) 40 kmph (c) 50 kmph

Figure 5 shows how well the current DNN and ANN models connect to the network. The vehicle had a fixed arrival speed of 30 to 50 kmph and a transmission range of 200 to 500 m. When the distance of a vehicle went beyond 400 m from the RSU the connection was lost, according to the simulation results, and the chance of connection decreased.

Figure 6 shows the comparison of the average data latency of the automobiles based on their velocity. The simulation's results demonstrated that speed increases were accompanied by an increase in data transmission delay. However, as the network density increased, the latency kept rising.

The highest latency was a result of the combined increases in speed and vehicle density. Because there is no established link between the automobiles, such mobility impairs data transfer.

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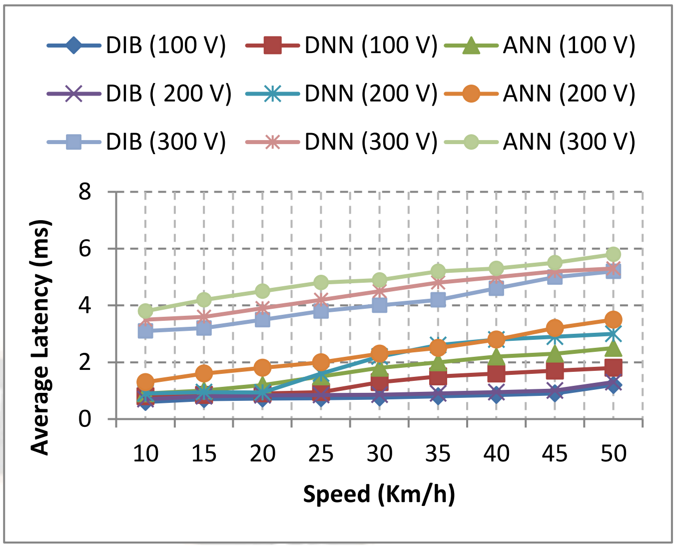

Figure 6. Speed vs Average latency

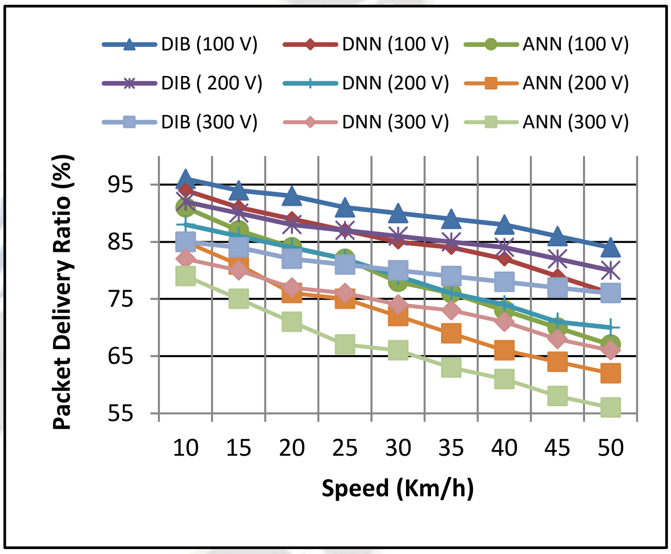

Figure 7. Packet delivery ratio vs Average latency

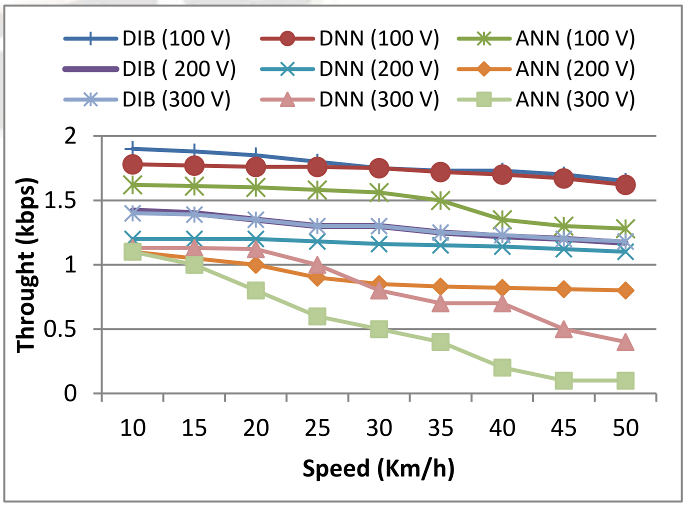

Figure 8. Speed vs Average latency

Since the average latency is inversely proportional to the PDR, this directly influences the delivery rate. On the other hand, the simulation results showed that the link was stable, with low vehicle density and speed, and as a result, the average latency was significantly reduced.

Figure 7 shows the outcomes of the packet delivery ratio at various vehicle speeds. A connection failure caused by the increased speed had an impact on the packet delivery ratio since the transmitters were unable to send the packets to the nearby VU. The packet loss stimulus rate and consequent performance were both significantly impacted by the connection failure. The overhead network's functionality was reduced as a result of the collision of the data packets, which raised the loss rate of the packets with a rise in vehicle density. According to the simulation findings, the DIB is more feasible than ANN and DNN.

Figure 8 depicts the results of the velocity at various data rates. The data rates change depending on the network density and the vehicle speed. As a consequence of the simulation result, the maximum throughput is obtained at the edges and curves of the highway, where the vehicle travelled at the slowest possible speed.

V. CONCLUSION

This research demonstrates that DIB provides effective vehicle routing with high-speed routes on VANETs. The greatest approach to increase energy efficiency can be obtained using DIB. To determine the mobility conditions of each vehicle in VANETs, DIB analyses the whole network. The routing choices were effectively handled by the DNN and offer a solution to deploy the best routes, hence reducing the overcrowding of the network more rapidly. At RSUs, the routing table is employed for updating vehicle data periodically, which enables the reliable routing selections. The DIB model has greater connectivity, end-to-end latency, packet delivery and throughput according to simulation data. In the future the traffic management in VANET may employ the additional deep learning algorithms that consider both vehicles and mixed traffic data.

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