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Ubiquitous Vehicular Ad-Hoc Network Computing Using Deep Neural Network with IoT-Based Bat Agents for Traffic Management

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Abstract: In this paper, Deep Neural Networks (DNN) with Bat Algorithms (BA) offer a dynamic form of traffic control in Vehicular Adhoc Networks (VANETs). The former is used to route vehicles across highly congested paths to enhance efficiency, with a lower average latency. The latter is combined with the Internet of Things (IoT) and it moves across the VANETs to analyze the traffic congestion status between the network nodes. The experimental analysis tests the effectiveness of DNN-IoT-BA in various machine or deep learning algorithms in VANETs. DNN-IoT-BA is validated through various network metrics, like packet delivery ratio, latency and packet error rate. The simulation results show that the proposed method provides lower energy consumption and latency than conventional methods to support real-time traffic conditions.

Keywords: deep neural network; VANETs; routing; IoT agents

1. Introduction

Vehicular Ad-hoc Networks (VANETs) are an important class of ubiquitous computing, which operate as a key technology for enabling the VANET applications [1–4].

VANETs have recently provided their users with the means for safety management and data management, where the control methods are designed to work under any circumstances based on network dynamics [5]. On the one hand, the use of centralized [5] and distributed algorithms makes traffic management more complex one regarding the increasing adoption of vehicles in VANETs. On the other hand, the increase in traffic affects urban transport indirectly, and it increases the delay in transportation, fuel consumption, and emission values [6].

Even in real-time with precise traffic flow predictions, the traffic management systems in VANETs often play a vital role in predicting the traffic flow. The Intelligent Transport

System (ITS) offers reliable traffic management services in such scenarios, enabling the user to coordinate the network in an optimal and safer way, to understand the environment. ITS information and communication technologies further enhance the management of traffic and mobility [5].

In order to ensure efficient and secured transmission, ITS strongly supports communication within VANETs between road units (vehicles) and roadside units (RSU). Several other challenges, such as limited scalability, flexibility, poor connectivity, and inadequate intelligence, lead to delays in time and congestion in communication channels, which significantly affect the performance of VANETs.

Various investigations are conducted in the existing literature [7–9] to solve such complexities in traffic management. These methods are used to solve the traffic congestion in VANETs, including difficulties in scalability, performance, and management. Several optimization tasks are undertaken in order to ensure the regulation of traffic flow dynamics in an urban scenario [10].

Congestion regulation is limited in existing methods in terms of accuracy and timely traffic predictions. The congestion effects in VANETs are treated as a classification problem and various solutions are offered, but the majority of systems are not fully usable [11,12]. The ITS systems support traffic predictions by analysing the network parameters to mitigate these limitations [13]. The predictions involve route planning and reprogramming to reduce the rate of congestion [14,15]. Furthermore, the stochastic and non-linear traffic characteristics [16] and traffic-flow are challenging to predict [17]. VANET methods traditionally use linear and machine traffic-flow prediction models based on network density, which fail to interpret the non-linear uncertainty [18–20]. Moreover, researchers are attempting to further apply this proposed method to practical, artificial-intelligence-based approaches based on optimization, metaheuristics, machine learning, and deep learning [21–44].

With exponential traffic growth and high computational resources, traffic management analysis becomes complex [45]. Therefore, a high-end intelligent system is needed for flexible and smoother transmission in vehicles with various constraints, such as uncertainty, exponential growth, and high computational resources. A high-end system uses deep learning models to manage network abstraction and resource optimisation. Researchers are developing various security-based protocols [46–58] and machine learning techniques [59–62] for different applications for wireless communication and data prediction.

With this motive, we introduce the Bat Algorithm (BA) [63] as a vital factor and provide inputs that enable the Deep Neural Network (DNN) routing algorithm to make optimal decisions. In this respect, this paper presents the following contributions:

1. In terms of various collision prevention methods, such as packet delivery rate, latency, failure rate, and real-time traffic throughput, the authors analysed the DNN-Internet of Things (IoT)-BA model with existing deep learning models;
2. The authors devised and updated the routing table to reduce vehicle collision rates in real-time based on the traffic information collected by the IoT agents across the network;
3. In order to improve VANET routing in a real-time scenario, the authors combined the Deep Neural Network [64–68] algorithm with BA. In regular cases, this ensures optimal routing decisions based on IoT-BA inputs, ensuring better service delivery through the mobile ad hoc networks (MANETs).

The outline of this paper is as follows: Section 2 provides the network model. Section 3 deals with the traffic management model. Section 4 evaluates the traffic management model with existing models. Section 5 concludes the paper.

2. Network Model

Figure 1 shows the network model under Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) entities. The following are the entities used to design the VANET infrastructure [69–72].

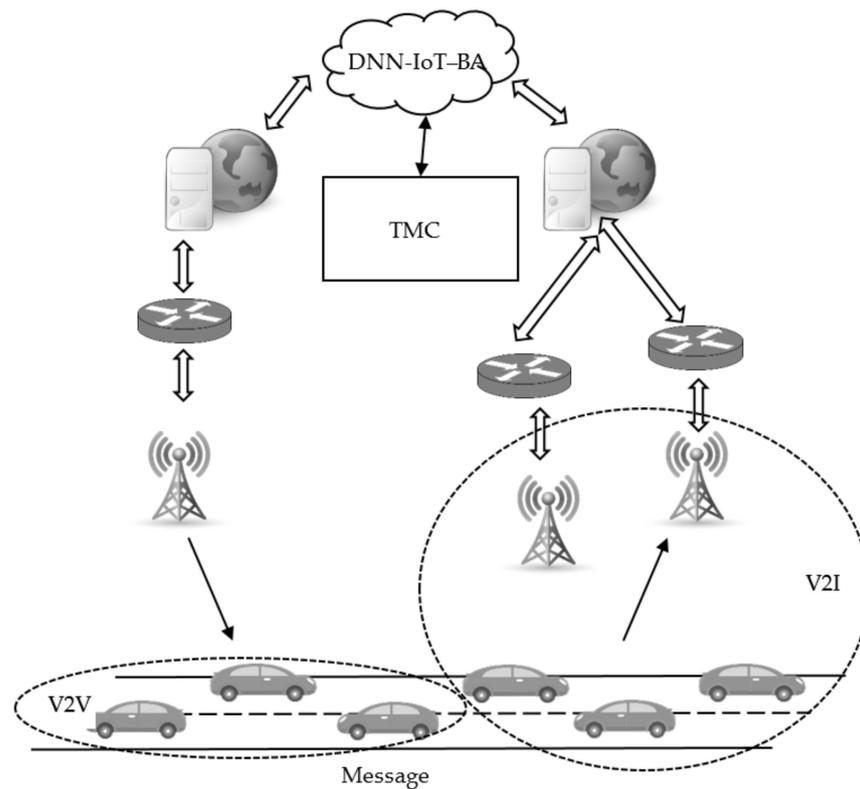


Figure 1. Vehicular Adhoc Networks (VANETs) model.

- **Vehicle Unit:** VANETs are responsible for communication with nearby vehicles along the highway sector or with the RSUs at the edges/corners in simple terms for transport purposes. VANETs are also responsible for facilitating transport. We used elliptical curve encryption as an encryption algorithm in this paper to generate cryptographic credential information and store it in the vehicle. The Global Positioning System (GPS) is responsible for locating the vehicle inside. In a road segment, RSUs can determine the total number of vehicles using a GPS unit [40–44,73–77];
- **Roadside units (RSUs):** The RSU is an access point on the roads, where details of vehicle units can be found along the roads. The vehicle units' encrypted street segments are regarded as the relay for the Transport Message Channel. An IoT-BA is connected to RSU by a faster means of communication. The RSU operates the cryptographic credentials to decode vehicle information and the DNN-IoT-BA algorithm and stores them;
- **Traffic Management Center (TMC):** The IoT-BA calculates the traffic density using road segments. In order to obtain road traffic information, the directional connection of TMC to RSUs and other IoT-BAs are used. In order to avoid congestion in road segments, the IoT-BA transfers the collected information to the DNN. The differential between TMC and IoT-BA is that the former is a fixed segment and the latter is a network-wide mobile segment.

The proposed method was tested in an urban scenario that was designed as grids and intersections of roads. The path between any two crossings was considered to connect two or more street segments, such as the segment $s(i,j)$ and intersection $I(i) s(i,j)$, providing a collection of different characteristics, which include road widths and lengths, vehicle traffic density, and the number of roads between two intersections [78–80].

The unit has a unique identification number (ID), consisting of the location, direction, and speed of the vehicle. Vehicles automatically accessed the RSU to understand total crossroads, traffic segments, and congestion levels. This study used IoT-BA to provide more precise vehicle information than existing vehicle communication models. The DNN made

appropriate decisions by forming the graph $G = \langle V, E \rangle$ with V in the proposed method, as the intersections between the source, the destination vehicle, and E are considered the road segments connected to intersections in V .

The below definitions can be considered as parameters that append themselves for optimizing the DNN via BA:

- Detection range is defined as the communication region between the receiver sensitivity threshold of any two vehicles and the SINR, which are required for payload;
- Data Exchange range is defined as the communication region in which the data transmission takes place;
- Time before handover is defined as the communication region where the OBU prepares for handover;
- Time to handover is defined as the communication region where the actual handover takes place.

The minimum received power is defined as the minimum power a car requires to physically receive the signal from RSUs, which is defined below

$$\text{Min}(P_R) = 10^{0.1 \cdot \text{sat}} \quad (1)$$

where sat is defined as the minimum signal attenuation.

The detection range is defined as the minimum reception power needed to establish communication based on wavelength, transmitter power, threshold, and path loss coefficient

$$\text{Detection Range} = (\lambda^2 \max(p)) / (16\pi^2 P_R)^{1/\alpha} \quad (2)$$

where:

λ is the wavelength;

$\max(p)$ is the maximum level of transmission power;

α is defined as the minimum level of a path loss coefficient.

Network Dwelling Time (NDT) is defined as the inverse of mobility leave rate (μ_{ml}), where a Vehicle Unit (VU) is in the range of RSU, which is given by

$$\mu_{ml} = V * P / (\pi * A) \quad (3)$$

where:

V is the velocity of the VU;

P is defined as the Perimeter of an RSU;

A is defined as the area of an RSU.

$$\text{NDT} = (\mu_{ml})^{-1} \quad (4)$$

3. Traffic Management Model

The DNN-IoT-BA traffic management model operates as a driverless assistant system that uses IoT-BA to collect traffic information near the road segments and intersections and acts as a forwarder of data to RSU. The DNN-IoT-BA traffic management system is a distributed graph-based model with a set of vehicles (V) and edges (E). The IoT-BA sends the number of vehicles present in the road segment and the traffic congestion near the intersections and road segments. In the proposed method, VANETs work with the IoT-BA that assists the infrastructure unit and then connects with the vehicle unit for routing operations.

3.1. Mobile Agent Unit

The DNN-IoT-BA traffic management system works as an unmanned traffic assistant system that collects traffic information near the roads and intersections with IoT-BA, as a data transmitter to RSUs. A distributed graph-based model with vehicle set (V) and

edges (E) is the DNN-IoT-BA traffic management model. In intersections and on roads, the IoT-BA sends the total number of vehicles. The VANETs work with IoT-BA in the proposed method, supporting the infrastructure unit and connecting it to the vehicle for routing operations.

The IoT-BA in the proposed VANET architecture is a dynamic module moving into VANETs and connecting vehicle units with the infrastructure unit. The IoT-BA is made up of four segments: an identification unit, an execution code unit, a path unit, and a space unit of datum. In order to distribute the data packets from the sources of the source to the destination node through cooperative BAs via the selective routing track, the IoT-BA uploads vehicle information onto the DNN.

As IoT-BAs contain a wide range of information, each system has a unique identity. The data of current vehicles passing through a road segment are stored in the cloud, and the routing path is defined by DNN, which is a core indicator of packet transmission. Lastly, the data space stores the data from the car units completely. In this case, it is in the RSU Infrastructure Unit that the DNN routing path is found [68].

3.2. Infrastructure Unit

The infrastructure unit is located on the application level, and the routing path can be robustly calculated using the vehicle position and speed via DNNs (DNN architecture with optimization for BA in Figure 2). Figure 2 specifies the workflow of the infrastructure unit.

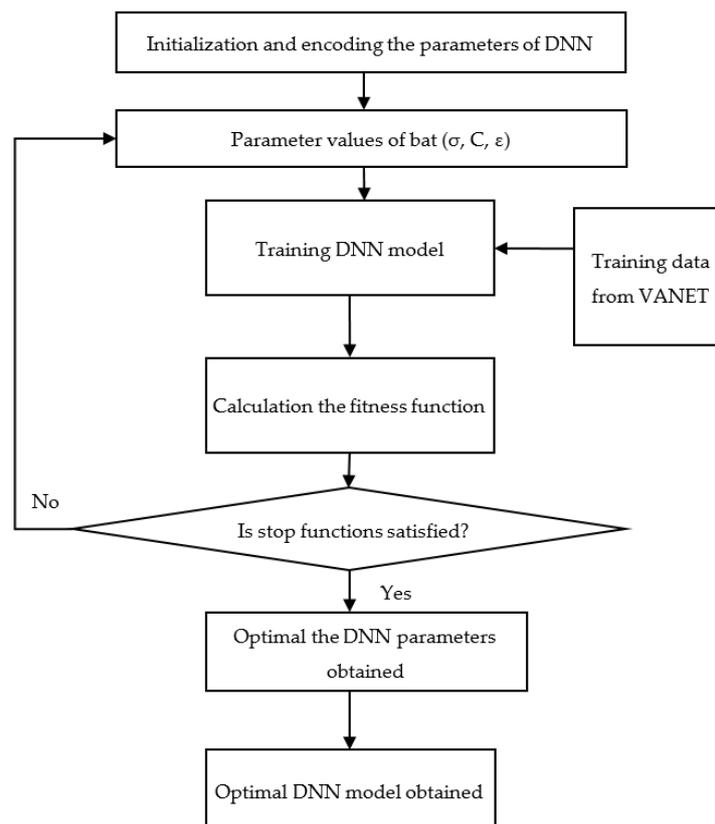


Figure 2. Deep neural network (DNN) architecture.

3.3. Bat Algorithm (BA)

The Bat algorithm emulates bat echolocation, whereby bats use echolocation to distinguish between prey and physical boundaries. Bats, additionally, identify differences in other ways, such as by flying in an arbitrary motion with speed v_i at position x_i , with a recurrence of f_{min} , turbidity A_0 , and shifting wavelength λ , in order to look for prey.

The bats alter the recurrence naturally, based on the radiated pulse, and this changes the pulse discharge rate $r \in [0, 1]$ based on the closeness of the fitness function. In general, the loudness varies between large A_0 (positive value) and a minimum A_{min} (constant value).

IoT-BA operations are defined in terms of their frequency, velocity, position, emission pulse rate, and loudness. These terms help the bats to search for prey in a D-dimensional space.

Virtual Bat Movement is obtained after the random initialization and the new position and velocity are updated in a regular time-step t , as below

$$f_i = f_{min} + (f_{max} - f_{min}) \times \beta \quad (5)$$

$$v_i^{t+1} = v_i^t + (x_i^t - x_*) \times f_i \quad (6)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (7)$$

where:

f_i is the frequency;

v_i^t is the velocity;

x_i^t is the position;

A_i^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.

For a local search, the solution is chosen based on the current best solution, and then the updated solution is locally produced for each bat based on the following condition

$$x_{new} = x_{old} + \varepsilon * A^t \quad (8)$$

where:

ε is the arbitrary vector;

A^t is the normal commotion at step t .

The global solution is updated with the best fitness function obtained from N bats when it is better than the previous best $f(x^*)$.

Loudness and Pulse Emission: A_i^t and r_i^t , respectively, tend to reduce and increase based on the rationalization of a new solution. This means the bats are moving in the correct direction towards their prey. This is formulated as shown below

$$If(rand(0,1) < A_i^t \&\& f(x_i) < f(x)) \quad (9)$$

$$f(x) = f(x_i) \quad (10)$$

$$A_i^{t+1} = \alpha A_i^t \quad (11)$$

$$r_i^{t+1} = r_i^0 (1 - e^{-\gamma t}) \quad (12)$$

where:

rand is considered a random vector with uniform distribution.

$0 < \alpha < 1$ and $\gamma > 0$

The negative Mean Absolute Percentage Error (MAPE) is used to enhance the weights and bias of the DNN in the form of a fitness function, which is provided below

$$MAPE = \sum_{i=1}^N \left[\frac{a_i - d_i}{a_i} \right] \times 100\% \quad (13)$$

where

a_i is the actual value;
 d_i is the estimated value.

The lower the MAPE, the better the optimization of parameters of DNN.

BA predicts the value of critical strength parameters in the VANET congestion detection process based on its operating of parameters and conditions. DNN uses the trained BA prediction to determine the values of process parameters that result in the optimal value of the strength parameters in various operating conditions.

3.4. Infrastructure Unit Workflow

The Infrastructure Unit (Figure 3) collects control information such as the position, location, speed, and time signature of the vehicle. The information is iteratively collected to ensure that the information is accurate. The data are gathered by the BAs and not directly transmitted to infrastructure units.

The information from IoT-BAs is sent to the DNN, and the routing path is processed based on the routing information collected from BAs (routing process is the same as in [64]). The BAs route BAs with a code execution unit and set the route to prevent the congestion of the VANETs. All operations are carried out to prevent the greatest challenge of congestion.

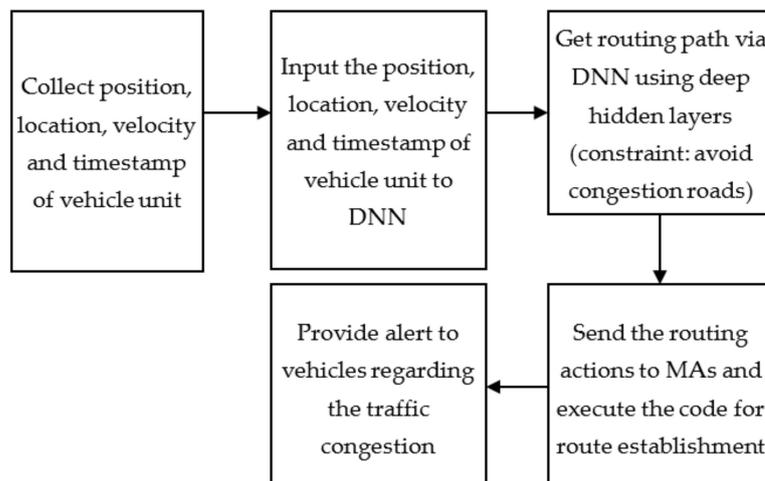


Figure 3. Infrastructure Unit Workflow.

4. Performance Evaluation

The DNN-IoT-BA was simulated in a python compiler (Anaconda with Python 3). DNN simulation parameters under VANETs are presented in Table 1. The simulation was performed on a two-way road with a fixed road width in an area of 1500 m × 1500 m. The simulation covered 300 vehicles in an urban scenario with speeds ranging from 0 kph to 50 kph. The IEEE 802.11p MAC protocol was used to estimate the packet interval and update the report on secured packet transmission. It also helped maintain the retransmission of packets that fail during the broadcast. The Krauß model was considered as the mobility model in the current study, which is a spatially continuous, car-following model, where the distance between the vehicles can be estimated by the VU itself. It further allowed the safe travel of VUs with proper velocity.

Table 1. Simulation Parameters.

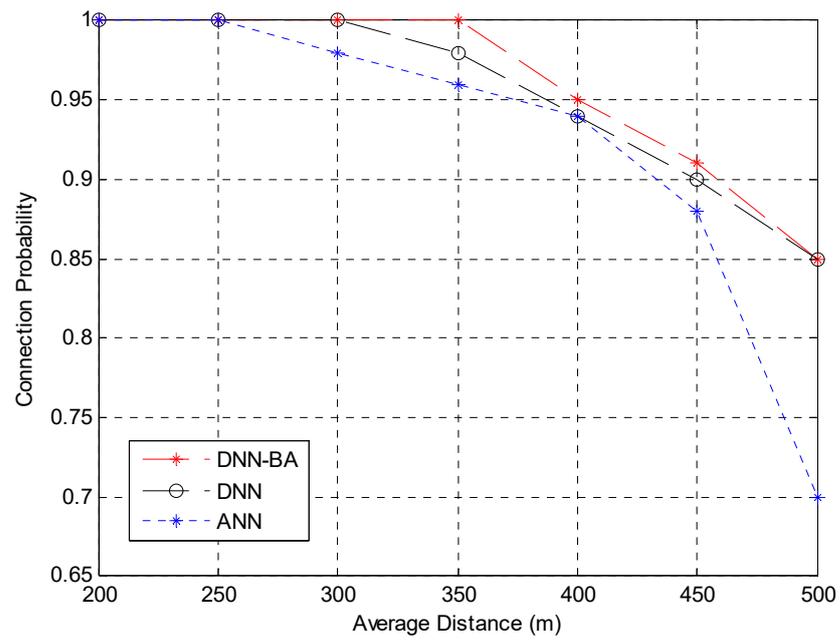
Parameters	Value
Total vehicle units	100–300
Channel carrier frequency	5.9 GHz
Packet length	Uniform
Maximum transmission	20 mW
Simulation area	1500 m × 1500 m
Vehicle velocity	20–50 kph
Bit rate	18 Mbps
Signal attenuation threshold	−90 dBm
Path loss coefficient	2
Transmission range	500 m
MAC protocol	802.11 p
Traffic type	CBR
Beacon interval	0.5 s
Data rate of MAC	6 Mb
Mobility model	Krauß model
CBR rate	4 packets/sec
Simulation time	1000 s

The validation of the DNN-IoT-BA proposed was conducted against the existing models of deep-learning: DNN and Artificial Neural Network (ANN) [65]. The DNN and ANN were trained without the predictions from BA and were trained directly with the proposed module without the inputs from BA. Validation was performed by different performance metrics, such as transport type, speed of the vehicle, and network density, to assess the average latency and cumulative distribution function (CDF).

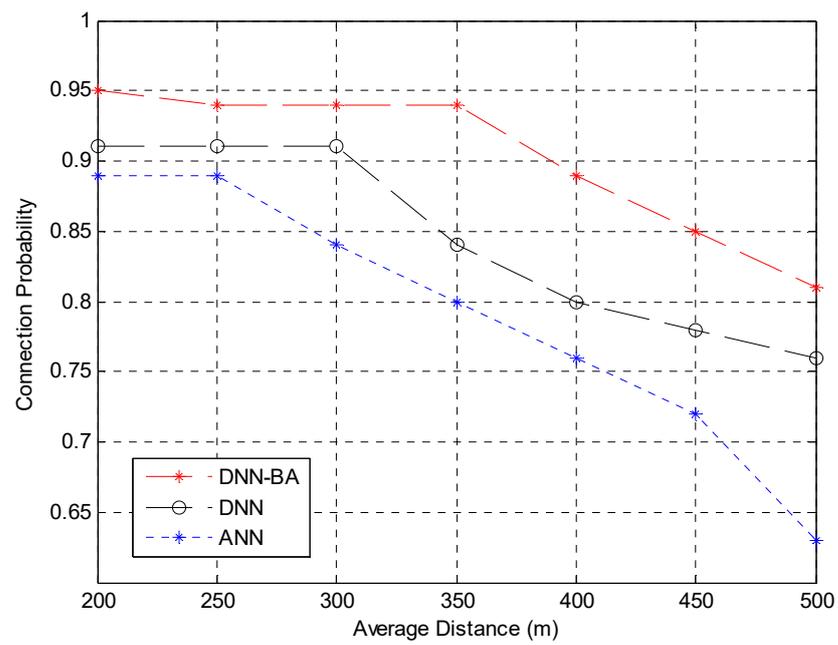
The network connectivity quality of the existing DNN and ANN models is illustrated in Figure 4. The transmission range varied from 200 m to 500 m and the vehicle's arrival rate was fixed from 30 kph to 50 kph. The simulation results show that the probability of connection expired with an increasing distance metric and the connection to a vehicle was lost when distance from the RSU was increased by 400 m.

Placing RSU on all 350 m, however, helped the VANETs build long-term connections with vehicles. Nevertheless, the connection probability still presented a challenge when connecting vehicles within the 300 m range (as illustrated in Figure 5), with increasing network traffic (from 100 to 300 vehicles). The CDF results from the DNN-BA, DNN, and ANN, testing the connection probability between 100 and 300 vehicles, are shown in Figure 5.

In this respect, the density of the network was high for 300 vehicles, mid-range for 200, and low for 100. The results show that a more distant connectivity to vehicles was established under the proposed method than using low-density models of DNN and ANN. Network degradation was shown when the density of the network increased.



(a)



(b)

Figure 4. Cont.

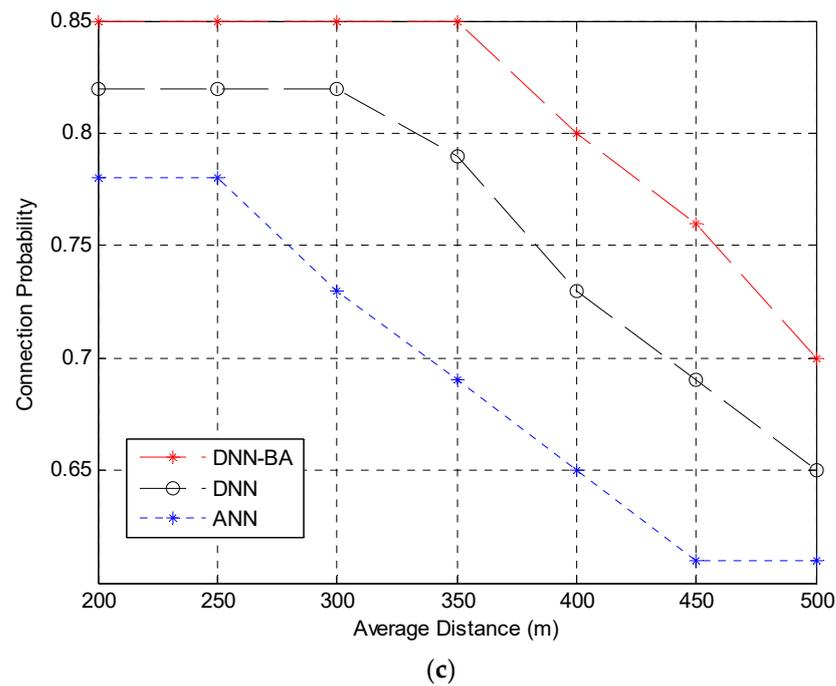


Figure 4. Network Connectivity vs. network density. (a) 30 kph; (b) 40 kph; (c) 50 kph.

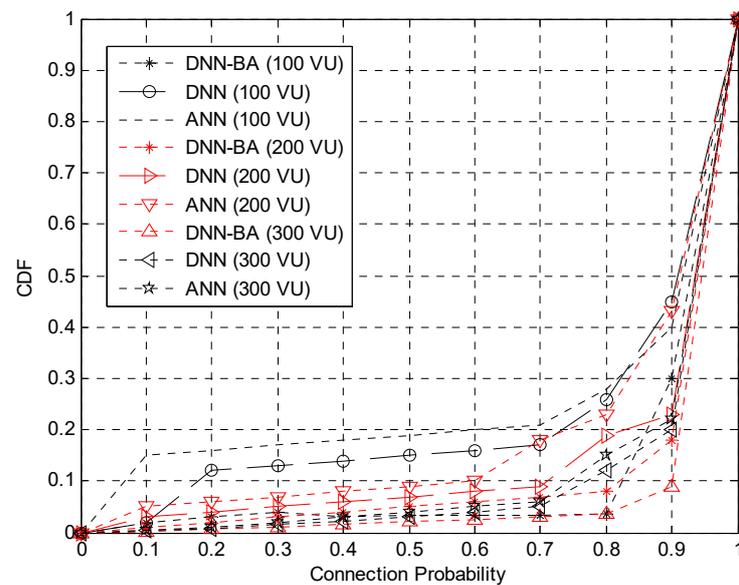


Figure 5. Cumulative distribution function (CDF) of successful connection (100–300 Vehicle units (VU)).

The results of the average data latency between the vehicles are shown in Figure 6, depending on their velocity. The simulation results show that data transmission latency increased alongside increases in speed. On the other hand, the latency continued to increase with increasing network density. The combined surges in speed and vehicle density contributed to the maximum latency. Such mobility affects the transmission of data because the link between vehicles is not established.

This affects the delivery rate directly because the average latency is indirectly proportional to the ratio for package delivery (Figure 7). The simulation results, on the other hand, show that the link was well established, with minimal vehicle speed and density, and the average delay was, therefore, significantly reduced. The DNN-IoT-BA performance was

efficient overall, due to the presence of IoT-BA, compared with the DNN and ANN, as the average minimum latency rate showed a lower failure rate.

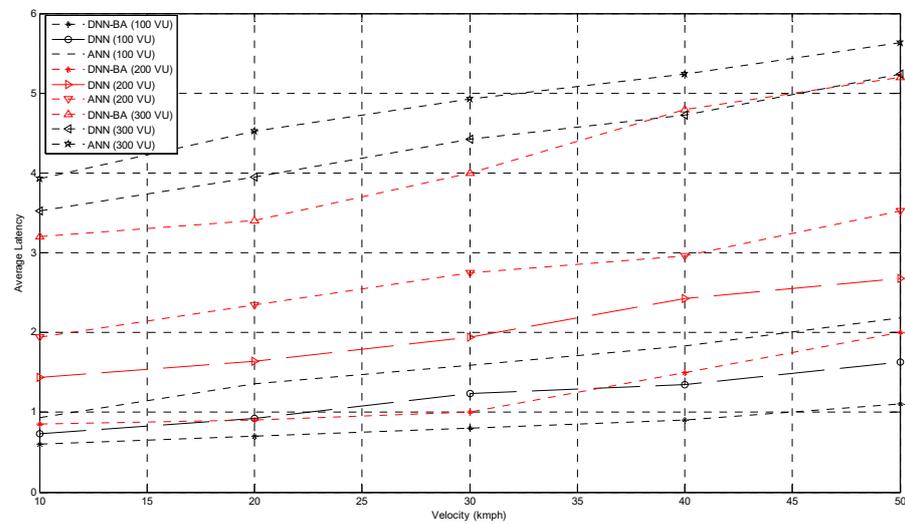


Figure 6. Impacts on average latency with variable velocity.

The results of the delivery ratio of packages with different car speeds and densities are given in Figure 7. As the transmitters failed to transfer the packets to the neighbouring VU, the packet delivery ratio was affected by a link failure due to increasing speed. Therefore, the connection breaks and the link with increasing network density exists. The break in connection had a significant influence on the packet loss stimulus rate, and thus on performance. The collision of the vehicle packets increased the packet loss rate with an increased vehicle density and resulted in a decreased functionality in the overhead network. The simulation results show that the DNN-IoT-BA was delivered with higher feasibility than DNN and ANN.

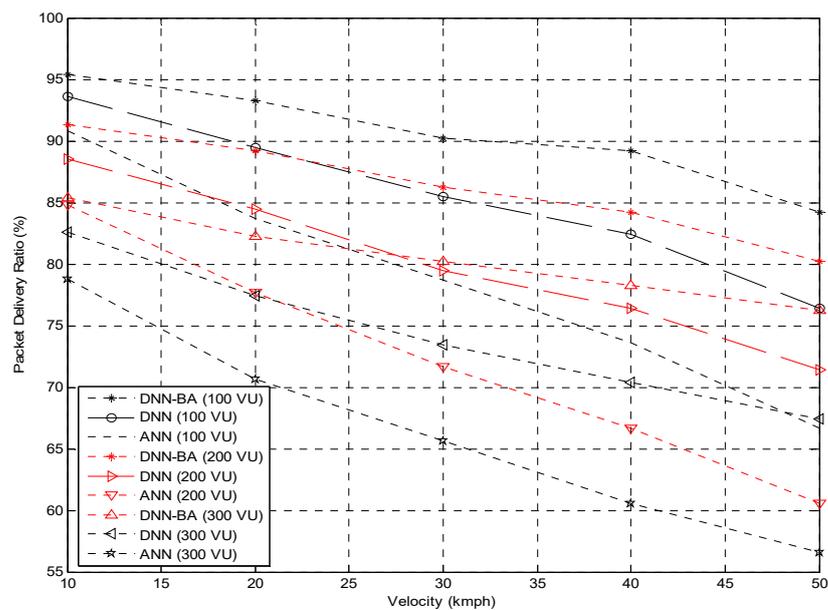


Figure 7. Impacts on packet delivery rate with variable velocity.

The results of the data with different data rates are displayed in Figure 8. The data rates vary according to the density of the network and the speeds of the vehicle. As a result of the simulation, the maximum output was achieved at the borders of roads,

as the vehicle moved in the direct and curved road sections with minimum speed and minimum throughput.

The DNN-IoT-BA also enhanced the network performance compared to other methods with the optimal choice of vehicles in road segments. The optimal selection reduced the packet loss rate, and the selection of the optimally adjacent vehicle hops effectively maintained the transmission connection. Due to the absence of an IoT-BA—in which vehicles can be used for determining a connection, and thus strictly prevent energy consumption by linking reliability—a throughput decrease was found in DNN and ANN. The determination of neural network parametric values by the BA assisted in improving the DNN optimization by finding the routes for the packets to traverse across the network.

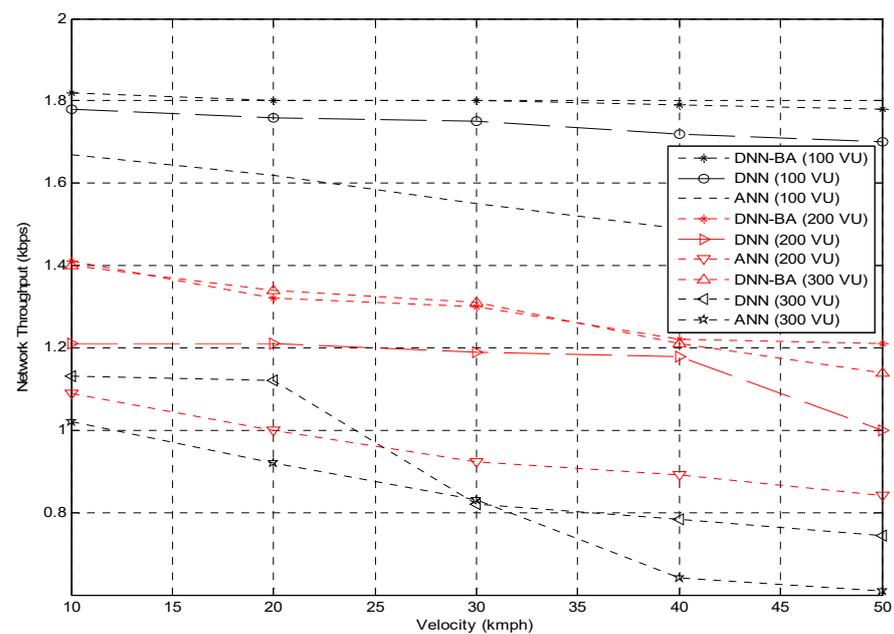


Figure 8. Impacts on throughput with variable velocity.

5. Conclusions

This paper shows that DNN-IoT-BA offers an efficient routing of vehicles on high-speed roads in VANETs. This DNN-IoT-BA is the best way of increasing energy efficiency. The IoT-BA examines the entire network to find the moving states of every vehicle in VANETs. The DNN-IoT-BA then optimizes routing decisions based on the MA inputs, with higher traffic congestions in the network. The DNN effectively processes routing decisions at a faster rate and provides a network solution to set optimum routes, thus reducing network congestion more quickly. The use of the routing table for regular vehicle updates at RSUs ensures optimal selection of vehicles and stable routing decisions. Data and transmission rates were demonstrated through variable speed, distance, and vehicle density, confirming that DNN-IoT-BA offers quicker routing decisions than existing DNN and ANN models. Simulation results show the higher connectivity, throughput, packet delivery, and end-to-end latency of the DNN-IoT-BA model. The results also show that the probability of connection termination in DNN-IoT-BA is lower, which supports increased data transmission. This means that simplified routing choices based on the continuous IoT-BA monitoring of DNN have optimally retained the traffic density, which ensures an efficient packet delivery to the destination nodes. Finally, the application of low-mobility vehicle routing decisions is efficient compared with those with a faster mobility of vehicles. In future, the application of other deep learning algorithms considering vehicles with mixed traffic data can be utilized for vehicular traffic management.

Author Contributions: Authors contributions are as the following: Conceptualization, S.K., G.D. and Y.N.; methodology, S.N.M.; software, A.S. and M.S.; validation, A.A. and M.G.; investigation, U.E.; resources, H.G.; writing—review and editing, M.G.; funding acquisition, H.G. All authors have read and agreed to the published version of the manuscript.

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