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Traffic management in vehicular adhoc networks using hybrid deep neural networks and mobile agents

Yassine Sabri[1], **Najib El Kamoun**[2]
[1]Laboratory of Innovation in Management and Engineering for Enterprise (LIMIE), ISGA Rabat, 27 Avenue Oqba, Agdal, Rabat, Morocco
[2]STIC Laboratory, Faculty of Sciences, Chouaïb Doukkali University, El Jadida 24000, Morocco

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ABSTRACT

The traffic congestion in vehicular adhoc networks (VANETs) is a vital problem due to its dynamic increase in traffic loads. VANETs undergo inefficient routing capability due to its increasing traffic demands. This has led to the need for intelligent transport system (ITS) to assist VANETs in enabling suitable traffic loads between vehicles and road side units (RSU). Most conventional systems offer distributed solution to manage traffic congestion but fail to regulate real-time traffic flows. In this paper, a dynamic traffic control in VANETs is offered by combining deep neural network (DNN) with mobile agents (MA). An experimental analysis is carried out to test the efficacy of the DNN-MA against conventional machine learning and a deep learning routing algorithm in VANETs. DNN-MA is validated under various traffic congestion metrics like latency, percentage delivery ratio, packet error rate, and throughput. The results show that the proposed method offers reduced energy consumption and latency.

Corresponding Author:

Yassine Sabri
Laboratory of Innovation in Management and Engineering for Enterprise (LIMIE)
ISGA Rabat, 27 Avenue Oqba, Agdal, Rabat, Morocco
Email: yassine.sabri@isga.ma

1. INTRODUCTION

In recent times, vehicular adhoc networks (VANETs) have offered safety management and data management to users, and they are designed with suitable control methods to operate on any circumstances to emphasize the network dynamics [1]. However, with increased vehicles, traffic management becomes complex with the use of both centralized [1] and distributed [2] algorithms. This indirectly affects urban traffic and increases intersection delays, fuel consumption, traffic accidents, and emission values [3]. Real-time and accurate traffic flow predictions often play a vital feature for traffic management systems. In such scenarios, the intelligent transportation system (ITS) offers reliable traffic management services that makes the users aware of the environment by coordinating the network in an optimal and safer way. Adoption of various information and communication technologies in ITS further enhances traffic and mobility management [1]. It highly supports communication in VANETs between the road units (vehicles) and roadside units (RSUs) for effective and safer transportation. Various other challenges lead to time delays and traffic congestion, which entirely affects the VANET performance. To resolve such complexity in traffic management, research has been carried out in existing literature [4–6]. These methods are adopted to resolve the traffic congestion in VANETs that includes scalability, performance, and management difficulty. Various optimization tasks are carried out that offer a major role in regulating dynamicity of traffic flows in urban scenarios [7]. However, the effects on congestion in existing methods are limited by offering accurate and timely information for traffic predictions. Most recently, the congestion effects are treated as a classification problem and wide-ranging solutions are offered, but most systems lack with limited usage [8, 9]. To support both limitations, the ITS systems supports the prediction of traffic conditions by analyzing various network parameters [10]. This prediction involves preplanning of routes and rescheduling that reduces the congestion [11, 12]. The stochastic characteristics [13] and non-linear traffic flow further poses a serious challenge to accurate traffic prediction [14, 15]. VANET methods use linear and machine learning models for traffic flow prediction based on network density that fails to read the nonlinear uncertainty of the system [16–18].

Traffic management analysis gets complex with exponential traffic growth and with high computational resources [19]. Hence, considering the uncertainty, exponential growth, and high computational resources, high-end intelligent systems are required for offering flexible and open architecture for smoother transmission of vehicles. The high-end intelligent system adopting deep learning models has the ability to manage network-level abstraction and optimization of resources. With such motivation, we introduce mobile agents (MA) [20] as a vital factor to sense the environment and provide inputs to offer optimal decision-making to the deep neural network (DNN) routing algorithm. The main contributions of this paper include:

- The author devised a scheme that senses the VANET environment in real time and updates the routing table at rapid instances to reduce the vehicle collision rate.
- The author combined the DNN [21–25] algorithm at regular instances, thereby ensuring better delivery of services across mobile adhoc networks (MANETs).
- The author evaluates the DNN-MA model with existing deep and machine learning models in terms of various collision avoidance metrics like packet delivery rate, latency, error rate, and throughput in a real-time traffic scenario.

The outline of this paper is as: In section 2 discusses the network model. Section 3 provides the details of traffic management systems. Section 4 confers the details of DNN-iterative algorithm (DNN-IA) architecture for VANET routing. Section 5 concludes the entire work.

2. NETWORK MODEL

Figure 1 shows the VANET network model with two different entities: vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I).

- Vehicle units: the vehicle units or vehicle in simple terms is responsible for transportation purpose and is utilized by VANETs for communicating with nearby vehicles along the road segment or with the RSUs at the edges/corners. In this paper, we use elliptical curve cryptography as an encryption algorithm to generate cryptographic credentials and storing in the vehicle. The global positioning system (GPS) can find the vehicle location. The total number of vehicles in a road segment can be determined by RSUs using a GPS unit.
- RSUs: The RSU acts as an access point which is deployed along with the roads, and it holds the details of vehicle units along with the road segment. The encrypted road segments by the vehicle units are considered as a relay for a traffic message channel (TMC) or an IA. An MA is connected with RSU via a faster communication medium. The RSU functions to run and store the cryptographic credentials to decode the vehicle information and the DNN-IA algorithm.
- TMC or IA: The MA uses road segments to calculate the traffic density. The direction connection of TMC with RSUs and also with other MA obtains information about traffic on the road segment. The MA sends the information collected via MA to DNN, which makes optimal routing decisions to avoid congestions on road segments. The difference between a TMC and an MA is that the former is a fixed segment and the latter is the mobile segments that traverse the network.

The proposed method is validated in an urban scenario, and is designed in the form of grids with road segments and edge intersections. The road between any two intersections is considered as the road segment s(i,j) and the intersection I(i) connects two or more road segments. s(i,j) is a collection of various features that includes width and length of road between two intersections, density of vehicular traffic, and number of lanes. The vehicle unit is designed with a unique ID (UID) that consists of its location, direction, and vehicle velocity. The vehicle accesses the RSU automatically to know the total intersections, road segments along the path, and the traffic congestion level. In such cases, the study uses MA to provide precise information about vehicles rather than existing data communication between the vehicles. In the proposed method, the DNN makes proper decision-making by forming a graph $G = \langle V, E\rangle$ with V as the intersections between the source and the destination vehicle and E as the road segments connected with intersections in V.

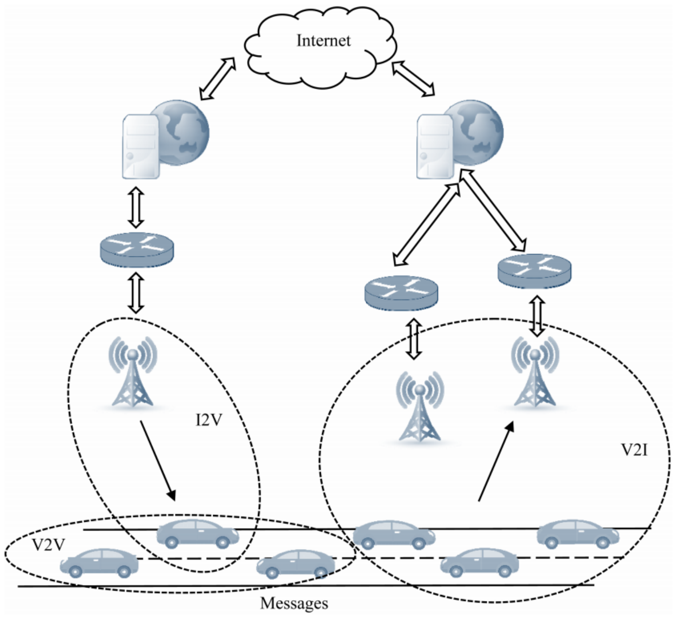


Figure 1. VANET model

3. TRAFFIC MANAGEMENT MODEL

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

3.1. Mobile agent unit

The MA in the proposed VANET architecture is a network module that dynamically moves inside VANETs and it accesses the vehicle units to get connected with the infrastructure unit. The MA consists of four segments, namely: the i) identification unit, ii) execution code unit, iii) routing path unit, and iv) data space unit. The MA uploads the vehicle information to DNN that offers faster computation to distribute the data packets from source to destination node via cooperative MAs by the selective routing paths. Since each MA has varied information; therefore, it is provided with a UID. The data of current vehicle passing a road segment is stored at the executive code and the routing path established by DNN is the core that indicates the traversal of the packet. Finally, the data space entirely stores the received data from the vehicle units. Here, the routing path using DNN unit lies in RSU infrastructure unit [21].

3.2. Infrastructure unit

The infrastructure unit lies at the application layer and calculates the routing path via DNN (the architecture of DNN is given in Figure 2) using the vehicle location, positions, and velocity in a robust way. The workflow of infrastructure unit is specified in Figure 3. 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 building automation (BAs) and not directly transmitted to infrastructure units. The information from internet of things-BAs (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 [24]). 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.

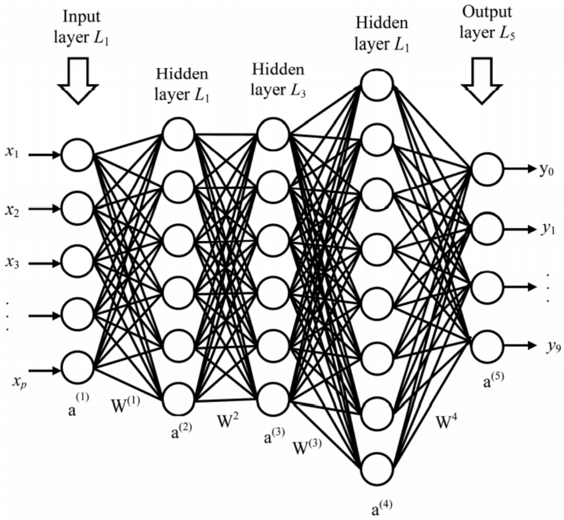


Figure 2. DNN architecture

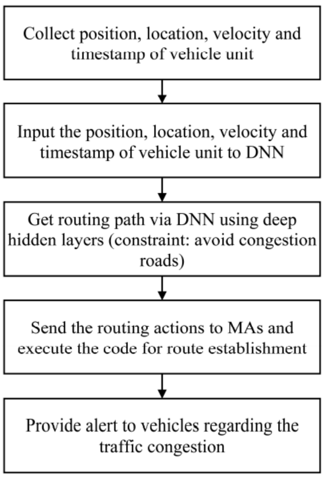
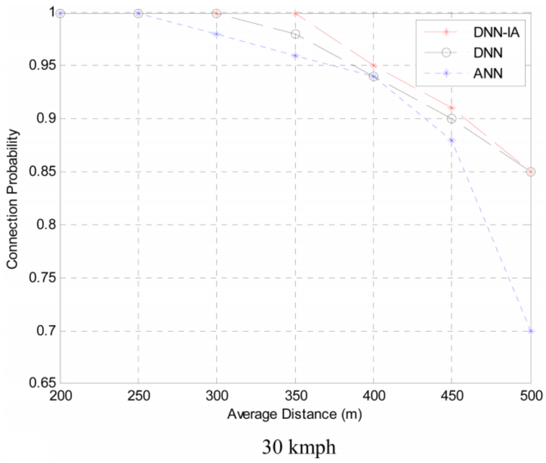
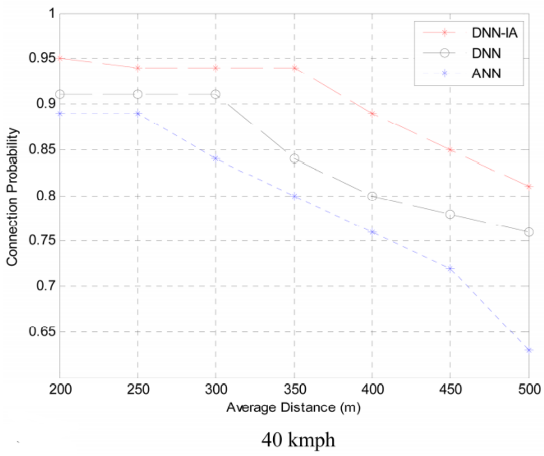


Figure 3. Infrastructure unit workflow

The validation of the DNN-IoT-BA proposed was conducted against the existing models of deep-learning: DNN and artificial neural network (ANN) [25–31]. 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) [32–36]. The network connectivity quality of the existing DNN and ANN models is illustrated in Figure 4. In Figure 4a the transmission range varied from 200 m to 500 m and the vehicle's arrival rate was fixed from 30 kph to 50 kph. (as illustrated in Figure 4b) 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 (as illustrated in Figure 4c). 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.



(a)



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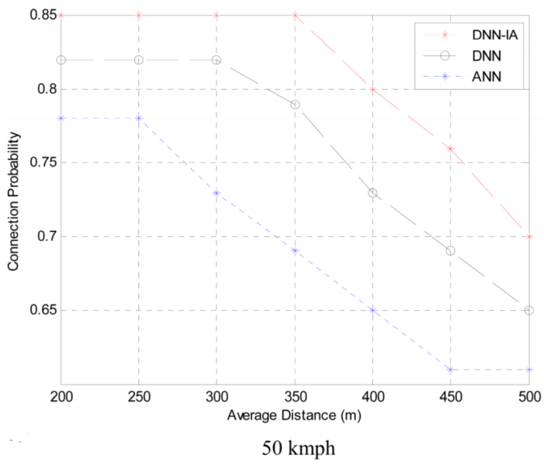

(c)

Figure 4. Analysis of connectivity probability (a) network connectivity, (b) varying distance, and (c) network density

The infrastructure unit is designed to collect the control information like position, location, velocity, and timestamp of vehicle unit. The collection of control information is carried out in an iterative way such that the information collected is precise. The information is collected by the MAs and it is not directly sent by the vehicle units to infrastructure units i.e. RSU. The data from MAs is sent as input to the DNN model and it processes the route establishment (the routing process is the same as that carried out in [22]) and forwards the routing details to MAs. The MAs then make the routing actions to MAs using code execution unit and then establishes the route to avoid congestion in VANETs. In this way, the entire operation is carried out such that the major challenge of congestion is avoided strictly.

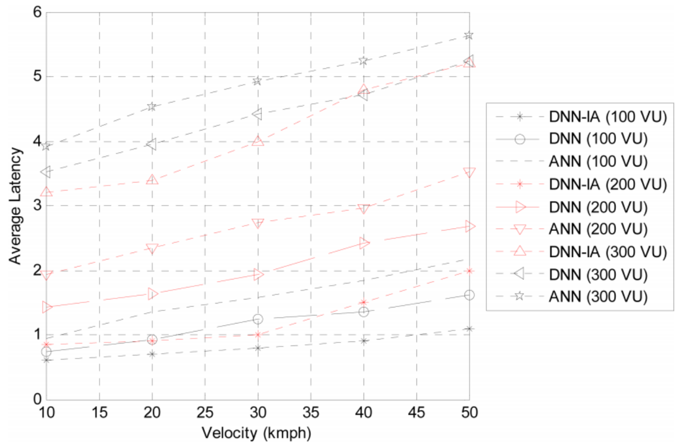

Figure 5. Impacts on average latency with variable velocity and network density

4. PERFORMANCE EVALUATION

The DNN-MA is simulated in a Python simulator and the parameters for simulating the DNN under VANETs are given in Table 1. The simulation is carried out in an area of $1500 \times 1500 \text{ m}^2$ in a two-lane road of fixed road width. The study covers 200 road edges and 250 road segments, where 170 road edges have traffic signals. The simulation covers 500 vehicles with a speed varying between 0 and 50 kmph (kilometers per hour) in an urban scenario.

The validation of proposed DNN-IA is carried out against existing deep learning model: DNN [20] and a machine learning model: ANN [21]. The validation is carried out over various performance metrics like traffic type, vehicle speed, and the density of network to evaluate the average latency, CDF, energy efficiency, packet delivery rate, and network throughput. Figure 4 shows the quality of network connectivity between the DNN-IA and existing DNN and ANN models. The range of transmission is varied between 200 and 500 m and the arrival rate of the vehicle is kept fixed at between 30 and 50 kmph. The simulation result shows that with increasing distance metric, the probability of connection expires and the connection with vehicle gets lost with further increase of distance from a RSU 400 m. However, the placement of RSU at every 350 m helps the VANETs to establish connection with vehicles over the long run. On the other hand, with increasing network traffic (from 100 to 300 vehicles), the connection probability still remains a challenge in establishing connections with vehicles lying within 300 m (which is evident from Figure 5). Figure 5 shows the results of CDF between the DNN-IA, DNN, and ANN, where the connection probability is tested between 100 and 300 vehicles. In this regard, the network density is labeled as high for 300 vehicles, medium for 200, and low for 100. The result shows that the proposed method establishes longer distance connectivity with vehicles than DNN and ANN models with a low density network. A degradation exists in the network when the network density increases.

Figure 6 shows the results of average latency of data transmission between the vehicles by varying the velocity of vehicles. The result of the simulation indicates that with increased velocity, the latency of data transmission increases. By contrast, with increasing network density, the latency increases further. The combination of both increasing velocity and increasing vehicle density contributes to maximum average latency. Such mobility impacts the data transmission due to the failure of establishing a link in forwarding the packets between the vehicles. This directly affects the delivery rate as the average latency is indirectly proportional to the packet delivery ratio (Figure 7). The results of simulation, by contrast, show that with minimal vehicle speed and density, the link is established well and hence the average delay is reduced considerably. Overall, the performance of DNN-IA is efficient in terms of minimal average latency rate with reduced failure rate due to the presence of MA than DNN and ANN.

Table 1. Simulation parameters

Parameters	Value
Total vehicle units	100-300
Channel carrier frequency	5.9 GHz
Frequency	5.9 GHz
Simulation area	1,500 m x 1,500 m
Maximum transmission	20 mW
Big rate	18 Mbps
Packet length	Uniform
Path loss coefficient	2
Signal attenuation threshould	-90 dBm
Vehicle velocity	20-50 kmph
Traffic type	CBR
Transmission range	150 m
MAC protocol	802.11 p
CBR rate	4 packets/sec
Beacon interval	0.5 s
Simulation time	1000 s
Data rate of MAC	6 MB
Mobility model	Krau model

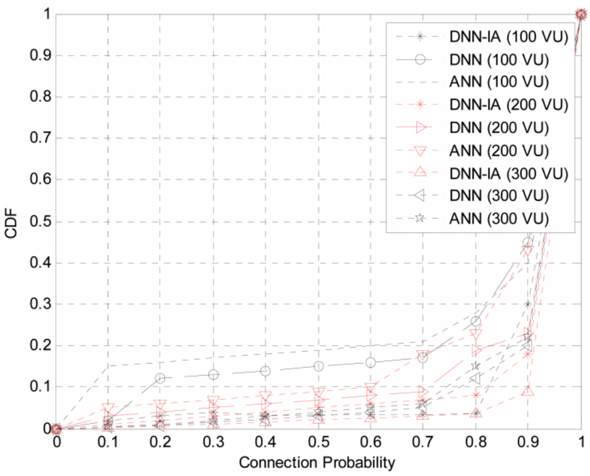

Figure 6. CDF of successful connection with varying network density (100–300 vehicle units (VU))

Figure 7 shows the results of the packet delivery ratio with varying vehicle speed and vehicle density. With increasing velocity, the packet delivery ratio gets affected due to a break in the link as the forwarders fail in forwarding the packets to the neighboring vehicle. Hence the link breaks and similar conditions exist with increasing network density. The link breakage highly influences the stimulus of packet loss rate and hence the performance is affected highly. On the other hand, with increasing vehicle density the collision of packets between the vehicles increases the packet loss rate and it affects the network overhead leads to reduced functionality. The result of simulation shows that the DNN-IA has a higher packet delivery rate than DNN and ANN with increased functionality. Figure 8 shows the results of throughput with varying data rates. The data rates are varied with respect to varying network density and vehicle velocity. The result of simulation shows that at the road edges, maximum throughput is achieved as the vehicle moves with minimal speed and minimal throughput at straight and curved road segments. Furthermore, the optimal selection of vehicles along the road segments by the DNN-IA has increased the network throughput than other methods. The optimal selection reduces the packet loss rate and selection of optimal adjacent vehicle hops effectively maintains the transmission link, thereby the throughput is highly consistent and energy efficiency is high. The throughput degradation is found in DNN and ANN due to the absence of MA in denoting which vehicle can be used to establish the link and, thereby, the energy consumption is avoided strictly on link reliability.

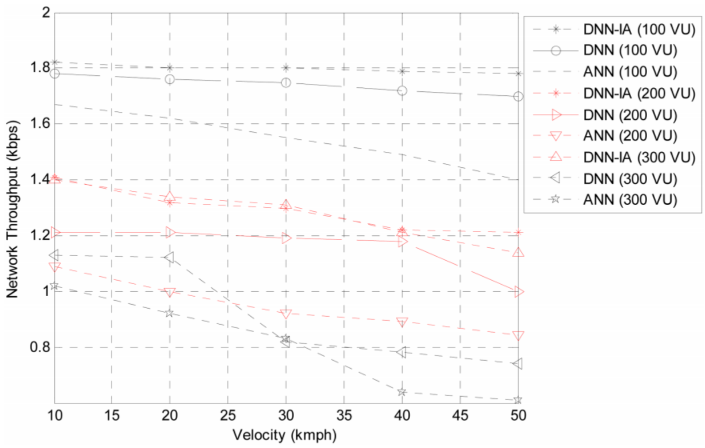

Figure 7. Impacts on throughput with variable velocity and network density

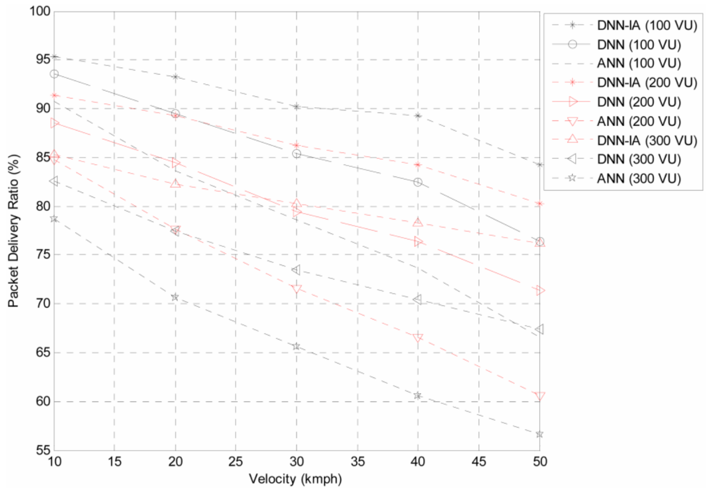

Figure 8. Impacts on packet delivery rate with variable velocity and network density

5. CONCLUSION

In this paper, DNN-MA provides effective routing of vehicles under highly congested routes in VANETs. This DNN-MA used in this paper offers optimal paths to increase the energy efficiency rate. The deep learning-based MA examines the entire network to find the states of each vehicle moving in VANETs. Higher traffic congestion in the network allows the DNN-MA to optimize the routing decision based on the inputs from MA. The DNN processes effectively the routing decision at a faster rate and provides a solution to the network in setting the optimal paths such that the congestion in the network is reduced in a faster instance of time. The utilization of the routing table at RSU for regular updates on the vehicle's state ensures optimal vehicle selection and stable routing decisions. The validation under variable velocity, distance, vehicle density, and data and transmission rate shows that the DNN-MA offers faster routing decisions than existing DNN and ANN models. The results of simulation show that the DNN-MA model has increased connectivity, throughput, packet delivery rate, and end-to-end delay and reduced latency. The result further claims that the connection termination probability is lesser in DNN-MA that supports increased data delivery rate. Thus, the simplified routing decisions using DNN based on constant monitoring by MA have maintained the traffic density in an optimal way and this ensures efficient delivery of packets to the destination nodes. Finally, the applicability of routing decisions on low mobility vehicle is more efficient than the one with faster vehicle mobility

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BIOGRAPHIES OF AUTHORS

Yassine Sabri was born on October 28th, 1984 in Rabat, Morocco. He received his fundamental licence (B.Sc), in the fields of science and technology and mathematics, from the Mohamed 5 University of Rabat, Morocco, in 2006. He completed his Master of Science (Msc), in the field of Engineering, from the Universiti Chouaib Douakaly in 2008 and then joined the Laboratory of Science and Technology to continue his studies to become a Doctor of Technology (PhD) in the field of WSN Technology. In 2013, he joined the Department of Science and Technology at ISGA Rabat as an assistant professor. His research interests include wireless sensor networks, evolutionary computation, the internet of things (IoT) and mobile computing. In recent years, he has focused on the processing of cloud computing, big data, artificial intelligence, machine learning, evolutionary algorithms, and software frameworks. He has collaborated actively with researchers in several other disciplines of science and technology. He can be contacted at email: yassine.sabri@isga.ma.

Najib El Kamoun Is a professor at Faculty of sciences, Chouaib Doukkali University, El Jadida, Morocco. He is a researcher member of STIC laboratory and header of Network and Telecommunications team. His research interest includes: NGN, MPLS, networks, QoS in mobile networks and wireless networks. He can be contacted at email: Elkamoun@gmail.com.