A NEURAL NETWORK APPROACH TO BLOCK CHAIN-BASED MOBILE EDGE COMPUTING FOR VEHICULAR NETWORKS

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ABSTRACT – In recent years, vehicular ad hoc networks, or VANETs, have received a great deal of attention from both academia and industry because of their potential to provide users with services like entertainment and adaptive route selection. Autonomous vehicles interact with fixed infrastructures and one another as part of VANETs to share data. Cars are equipped with sophisticated sensing equipment called Application equipment (AU) and On-Board Units (OBU) that can communicate and process data. These devices can be used for a wide range of purposes, such as traffic management, alarm generation for community services, and comfort, safety, and security for passengers. The network may become clogged and overloaded as the amount of vehicle communications increases.

1 INTRODUCTION

The development of wireless communication technology and ubiquitous information distribution has led to the emergence of vehicle ad hoc networking (VANETs) as a viable means of providing real-time information to cars that enhance driver safety. Intelligent Transportation Systems (ITS) primarily consist of a self-organized, wireless network oriented service communication to distribute driver conditions of traffic prior to any potential interruption in cars and to obtain information related to safety in real time. Vehicle communications are becoming increasingly common due to safety requirements, thanks to investments made by automakers and public transportation providers. Vehicle area networks, or VANETs for short, are thought of as vehicle sensor networks that enhance road traffic safety by exchanging information between vehicles or connecting to roadside infrastructure.

In vehicle-ad hoc networks (VANETs), multi-hop wireless broadcasting has been proposed as a way to provide security applications with stringent quality of service (QoS) requirements, like low latency, high confidence, and scalability. However, in the urban transport context, message redundancy, severe channel contention, and complex road designs greatly reduce the effectiveness of multi-hop broadcasting. In this study, we suggest using a multi-hop broadcasting approach (UMBP) for metropolitan regions to send important messages. A unique forwarding node selection mechanism built into UMBP uses micro slots, black-burn, and iterative partitioning to efficiently choose a single forwarding node with an asynchronous dispute and to quickly choose distant neighbor nodes. Because of the location of the emergency transmitters, directional, multidirectional, and bidirectional broadcasting.

A neural network based on the information processing system is called an artificial neural network (ANN). Information processing systems are primarily characterized by their structures. Multiple interconnected neurons collaborate to address certain problems. They collaborate to operate. To create an ANN for a specific use case, like nonlinear process modeling, a learning procedure is used. Synaptic connections between neurons must be modified for learning to occur in biological systems. The word "weights" refers to these synaptic connections. Perceptron’s invented by Frank Rosenblatt are recognized as essential building blocks of artificial neural networks. Education, flexibility, generalization, storage, and other properties are all present in the three-layer MLP neural network. At the top is the layer of linear neurons. Prior to entering the buried layer, the input signals are preprocessed.

2 RELATED WORK

Isalehi Salehi (2012) The primary issues that lead to a network being divided are uneven energy consumption and load imbalance in numerous routing techniques. Furthermore, the network's lifespan and energy consumption would be impacted by the lower packet delivery ratio. Routing should be well handled, especially for the WSN, as it is a very important function. Setting up the right kind of communication between the sensor nodes and the intended recipient is crucial for data transmission. The network life will be shortened by this process as the number of wireless nodes increases. As a result, a number of routing protocols have been developed to reduce energy usage and extend network lifespan. Various routing protocols can be categorized based on how they work, which nodes they involve, and the network

Rajadurai & Jayalakshmi (2013) talked about the issues and risks that car networks face as well as potential solutions. Two protocol groups, LocVSDPs and GeoVCom, are recommended to form a safety development resolution group within VANET. Thus, the car serves as a communication node to protect accident prevention and warning and offers services like traffic information in order to assure safety. By using VPKI, a Group Signature, and a Regional Trusted Authority, the protocol improves VANET scalability and provides security.

Prathiba et al. (2014) have suggested a hybrid ANN based optimal power flow; however, deregulation validation is needed. Numerous disparities, including those involving active and reactive power flow as well as violations of magnitude and phase angles.

Ali Hezam Mohammed (2017) Inter-vehicle communication is made possible by the Vehicle Ad Hoc Network (VANET), a subset of the Mobile Ad Hoc Network that is essential to the planned Intellectual Transportation System and helps to overcome the shortcomings of the current communication infrastructures. Environmental factors have been found to be associated with vulnerabilities in Vehicle Ad-Hoc Networks (VANETs). VANET Security is therefore a crucial problem that has to be solved. We assess the safety risks associated with VANETs and discuss their challenges in this study. Additionally, we compare the attack types, security requirements, and attackers' abilities on VANETs.

The Julia Silva (2021) Researchers first started studying vehicle ad hoc networks (VANETs) in the early 2000s. The capability of communicating through.

3 MODEL AND METHODOLOGY SUGGESTED

To mimic this issue, a GPU server equipped with an Intel(R) Core(TM) i7-6600 CPU and 16GB RAM was utilized. Our software environment for the Windows 10 64-bit operating system is Tensor Flow 1.6.0 and Python 3.6. These two simulation tools have been widely used in academia and industry. An open-source machine learning software framework called Tensor Flow is widely used to create novel techniques and experiments in the field. We therefore verified that it is possible to predict and approximate the performance of our proposed BMEC-FV system in realistic networks. A number of VANET nodes and four RSUs will be present in the BMEC-FV simulation environment. Every RSU has an installed MEC server. We think that in the simulation, each of the four RSUs is a block manufacturer.

Table 1: BMEC-FV Simulation Parameters

Simulation Parameter	Assigned value
VANET Topology	Random and grid
Packet size	1024 bytes
IEEE 802.11 MAC	802.11p
Topology covered area in device layer	$5 \times 5km^2$
Data rates	5.5 Mbps
Mobility	Static (none)
Number of vehicles	32
Total channel number	10
Weight for VANET environment Ω	0.5
Weight for VANET environment Y	0.5
The block size	1Mb
Mini-batch size	32

The conventional neural network with ten hidden layers—the deep Q-Network—is used. (CNN). Specifically, we apply CNN pruning to improve training efficiency.

Three convolution layers, three max pooling layers, and two fully connected layers make up the target network in our simulation, along with a network for assessment.

The CNN strategy is to start cutting at 4000 steps, stop at every 100 steps in 2000 steps, and then resume cutting. The tapping technique in our simulation results in a binary mask variable being filled in each selected layer.

The layer is exactly the same in terms of weight tensor shape and form. The weight of the weight update is set by the mask variable. The mask update algorithm must insert the following in the TensorFlow calculation chart:

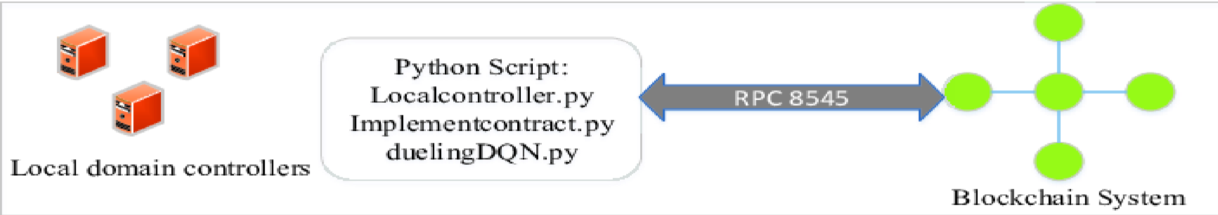

Figure 1: structure of the suggested BMEC-FV simulation

In our simulation, we have following systems Fog 2 to 7 showing the performance comparison.

The CNN DDQL-based plasticization strategy was proposed. In this system, each learning agent (RSU with the MEC server) selects the most reliable cars, a sufficient number of subsections, an ideal block size, and a number of successively generated component blocks for each replica.

This deep Q network is designed as a CNN with a tailoring technique. Compared to a traditional deep Q-network, CNN can perform function extraction more effectively, increasing training efficiency. So, the best outcomes should come from this approach.

A CNN and ten hidden layers neural system based on DDQL without pruning were proposed. Furthermore, the trustworthy vehicles, an appropriate number of sub-channels, the ideal block size, and the number of succeeding blocks generated per copy are all selected by this system.

The convergence of situations compared with duels deep Q-learning in the recommended approaches is shown in Fig. 2. The degree of Q-value adjustment is shown by the loss value L (figure).

The training loss is higher in early training due to the experience repetition group's rising experiences, and the deep neural networks (10 hidden layers and CNN) lack sufficient understanding of the unpredictable environment.

As the officer has sufficient experience, the training loss decreases concurrently. Such improved and reduced training loss performance demonstrates the usefulness of deep neural networks.

Additionally, we can see that our recommended pruning schemes outperform the pruning schemes in Fig.5. The cutting strategy reduces the amount of connections between the CNN network weights tensors by removing unnecessary weight values.

There are causes for the improved system performance, our proposed systems employ the RBFT consensus technique.

As opposed to the PBFT, the RBFT has developed several significant Transaction Verification connections that guarantee agreement on the sequence in which transactions are executed as well as the outcomes of block verification, enhancing consensus effectiveness and system performance.

Meanwhile, the proposed system makes use of dynamic adaptive sub-channel allocations, which could effectively reduce communication delays.

To enhance system performance overall, the proposed method may also change the number of blocks created and their sizes. Fig 4 illustrates the reward convergence performance of the DDQL-based scheme using a pruning strategy at different learning rates.

Fig. 5 shows how the mean transaction size and the BMEC FV system's performance are related. This graphic can be used to display the pro-position technique results with different transaction sizes that correlate to the offload jobs in BMEC-FV systems.

This chart illustrates how system performance declines significantly with increasing transaction average sizes.

There are two possible explanations. As transaction sizes increase, fewer transactions might be included in a block. Stated differently, they are significantly expanding the system's block count.

As more blocks are handled, the system performs less well. MEC system performance is decreased as a result of an increase in transmission time from VANET to RSU nodes.

The long-term benefits of the BMEV-FV system yield the highest long-term return when our idea is implemented. Because the number of fixed blocks cannot be guaranteed, the communication connection cannot be secure, and the transaction size is unpredictable, the current plans perform the worst.

The relationship between BMEC-FV performance and block chain request processing time is seen in Fig. 6. This graph illustrates how the longer-term benefit of the system increases and eventually remains constant as processing request delays increase.

To improve the BMEC-FV system's performance by reducing the penalties attached to rewards, we establish delay restrictions that handle requests that are delayed within the reward function's limitations.

The scalability of the BMEC-FV system is demonstrated by Fig. 7, which also demonstrates how the system can handle dynamic changes in the VANET node number.

In our simulation process, we first train four RSUs and 32 VANET nodes online using the BMEC-FV Framework.

This off-line training framework then processes the VANET environment, where the RSU number C is set at 4, and the VANET node U varies from 2 to 32. This indicates that the curve reached by this figure is obtained online.

This image suggests that while RSA can obtain the lowest feasible return, the recommended ways can obtain the longest-term payout even with a large number of VANET nodes. Although the present one is superior to the earlier one.

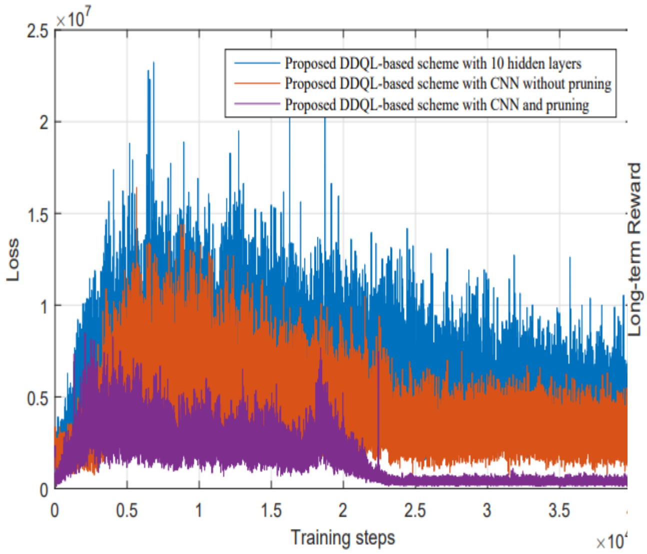

Fig 2

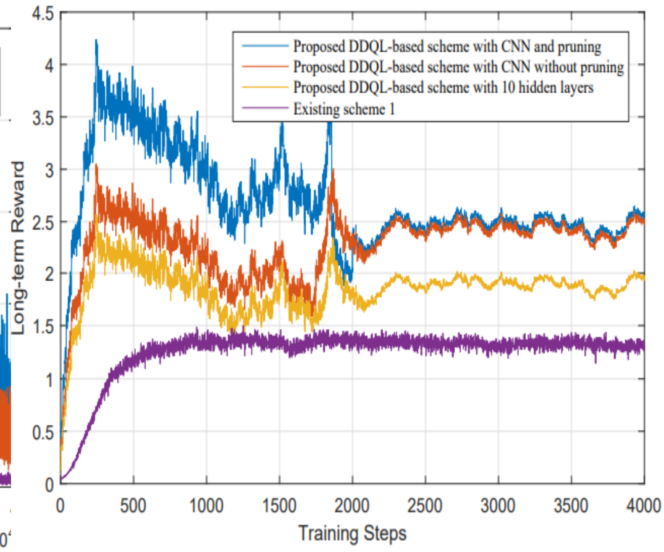

Fig 3

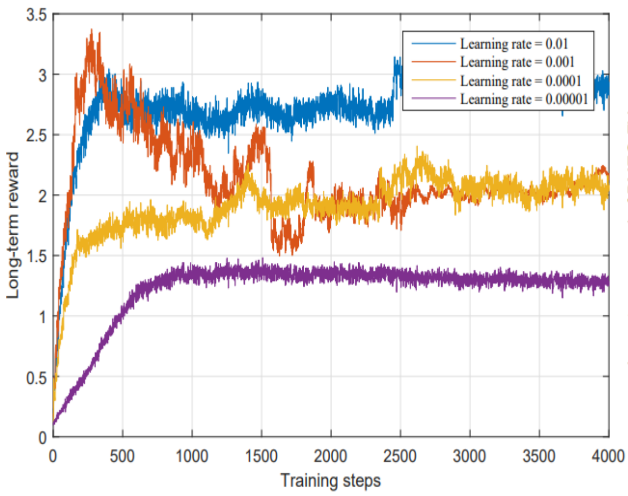

Fig 4

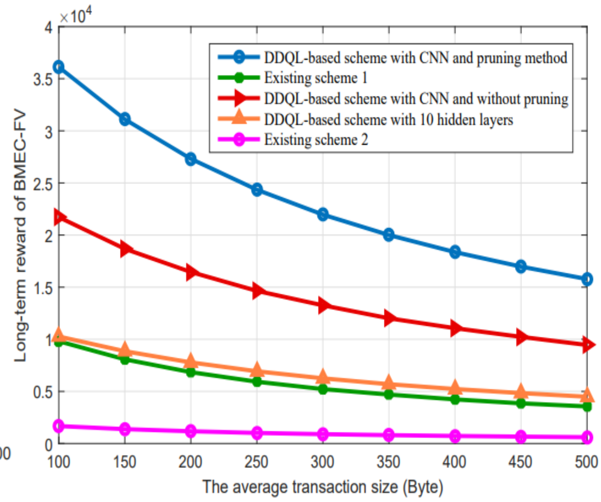

Fig 5

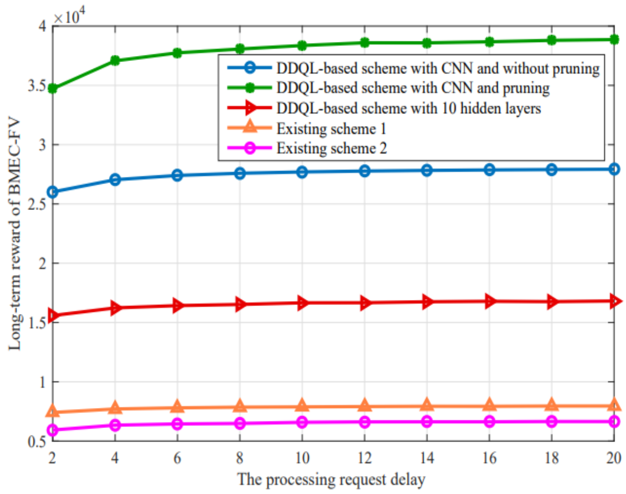

Fig 6

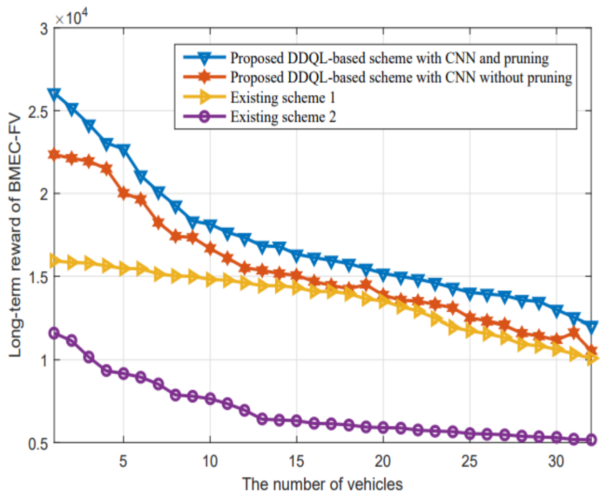

Fig 7

Figures 2 to 7: Showing the performance

Selection of the Ideal Route Using the Lion Algorithm:

Based on the Lion's natural behavior (Bauer et al., 2003), the Lion algorithm (Rajakumar, 2012) was developed in 2012. Like weak lions, disappear from the pool of possibilities because the answer—which could be a territorial lion—must be strong enough to thwart a random solution, which could be a migrating lion. The absence of some possibilities will lead to a superior solution (successful lion in territorial acceptance/defense), which will prevail over other options (laggard lion). This study uses the revised version of the proposed LA (Rajakumar, 2014) from the previous version (Rajakumar, 2012). The modifications included incorporating the stage of fertility evaluation, altering the crossover.

<u>Experimental Foundations for VANET-based trustworthy emergency message broadcasting system based on the Lion Optimization Algorithm (LOA):</u>

As a reliable and efficient broadcasting system, "ASPBT – adjustive scheduled partitioning and broadcasting technology" is anticipated to be used. For the transfer of private car data, this ASPBT is used with less delay. Unicast and multi-hop transmissions, as well as pure floods, are more suited for the distribution techniques. VANET contains the anticipated safety performance system. The Lion optimization method, a population-based meta-heuristic algorithm, is demonstrated through an analysis of lions' social behaviors. This algorithm could provide the results. It is the world's strongest animal, a lion, with fashionable social behaviors.

With 40 automobiles and 70 nodes in the network, it has been found that LA convergence is larger than GA. The two arcs first overlap and then diverge as the number of assessments rises. Reduced routing costs over GA are indicated by the LA curve's fastest concentration. The GA curve just slightly deviates from the LA curve as it bends beneath the latter. In network models 1, 2, 3, and, the corresponding routing costs for LA are computed at 0.95x106, 1.55x106, 2.4x106, and 3.6x106. With an increase in evaluations, the LA curve is continuously convergent in the network with 50 cars and 80 nodes, traveling parallel to the GA curve. Still, the two curves converge at 2.5

Table 2: Calculating the amount of time that LA and GA

Configuration	GA	LA
40 vehicles, 70 nodes	263.4403	98.9077
50 vehicles, 80 nodes	346.8884	115.7794
60 vehicles, 90 nodes	447.7318	134.142
70 vehicles, 100 nodes	560.5515	153.164

The amount of time needed to determine the best path for various network configurations by GA and LA.

The results demonstrate that using LA greatly reduces the calculation time for all network types. At least 60% of the computation time to discover the best method via the GA is recorded by the LA (approximately).

The cost of GA's network configuration route is reduced by 70% by LA up to a maximum. 4.

AQRV: Adaptive QOS-Based Routing Using ACO for VANETs:

VANETs are self-organizing wireless networks that use cars as servers and/or customers to communicate and transfer information. In this thesis, we mainly focus on the routing question. There are two types of routing protocols in VANETs that have been studied in detail: geographic routing protocols and routing protocols with a topological basis.

Node-to-node links provide information that topological routing protocols (like Toras or AODV's) employ to transfer data packets from the source to the destination. There are frequent link interruptions due to these conventional node-centered routing techniques.

Instead of requiring the upkeep of a whole routing database like GPSR, geographic routing methods employ the geographic position of the neighboring node to calculate the destination's next hop. In highly dynamic environments, geographic routing has proven to be more scalable and effective than topology-based routing. The field of geographical routing still faces numerous unsolved issues.

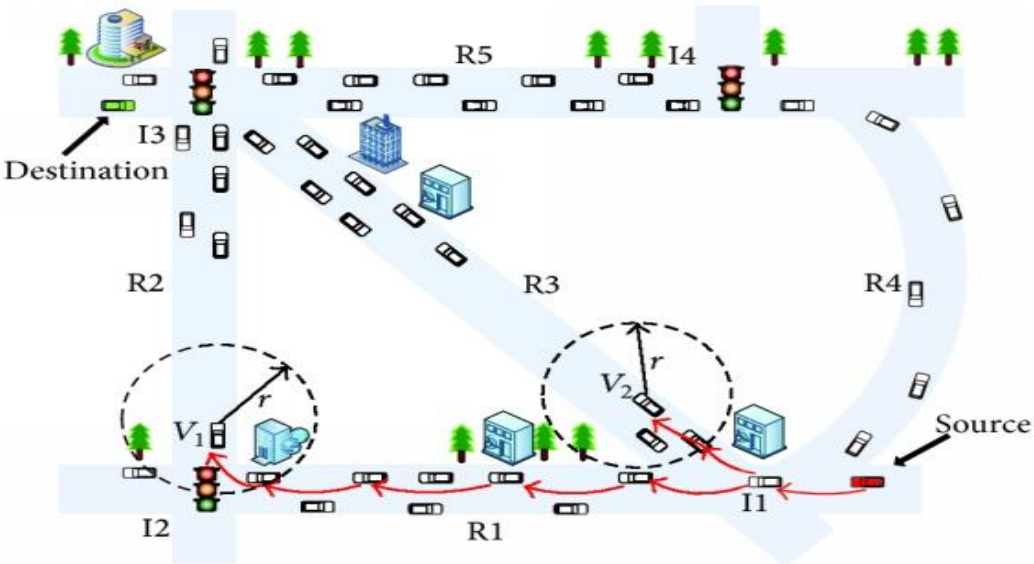

Fig 8: Showing routing issues with the VANET protocols currently in use.

Based on the above-mentioned analysis and debate, we suggest a novel routing protocol for VANETs with ACO dubbed Adaptive QoS-based routing (AQRV). Based on the ACO concept, AQRV integrates proactive and reactive elements to attain and preserve the best possible travel route.

The ideal path, which consists of a list of cross-sections between the source and the destination, is investigated by remote ants.

The primary feature of road selection is a highway sector relay quality that is routinely evaluated and represented by three combined quality of service (QoS) parameters: packet delivery ratio, latency, and connection likelihood.

AQRV uses proactive ants for proactive route maintenance, which updates, expands, and improves routing information. The next optimal intersection for data is chosen by AQRV.

Table 3: Configuration parameters for the simulation

Parameter	Value
Number of vehicles	150~ 400
Data packet sending rate DPR	5~ 15 packets/s
Periodic packet rate PR	1 packets/s
Data packet size	512 Bytes
Reactive forward ants N_{fant}	10
Reactive route exploration factor β	10
Proactive route maintenance factor β	5
Weight values of QoS metrics ϕ_1, ϕ_2 and ϕ_3	0.2, 0.2 and 0.6
Weight value of data process δ	0.3
Weight value of pheromone evaporation η	0.95

Table 4: The trust prediction model's simulation parameters

Parameter	Value	Description
Simulation time	100 seconds	The time for which simulation runs
Highway length	5000-15000m	The length of the road considered for simulation
Highway width	50m	The width of the road considered for simulation
No. of nodes	50-400	The number of vehicles
No. of Non-cooperating vehicles	5%	The vehicles refuse to participate in communication
Propagation radio Model	Two Ray Ground	Topological Model
Node placement	Random	Placement of nodes in network
Mobility Model	Random way point	Node movement model
Routing protocols	AODV,DSR,DSDV	The protocols for analysis
MAC protocol	IEEE 802.11p	IEEE standard for wireless communication
Transmission range	500m	Transmission range of vehicles
Base frequency	5.88GHz	Frequency used for simulation
Velocity range	10-30m/s	The velocity range of vehicles
Movement model	Dynamic	Node movement model
Traffic type	CBR(TCP)	Protocol for initiating communication
No. of simulation runs	10	Number of analysis runs

4. RESULTS & DISCUSSION

One can determine network efficiency by looking at the quantity of bad paths. A protocol that offers a high transmission rate over a network has fewer unstable pathways.

AODV-F performs better for route selection since the percentage of unstable routings is lower than 8.17 percent for DSDV-F and 3.97 percent for DSR-F.

Inconsistency exists among the unreliable nodes in the network and they are unlikely to be relayed. If the protocol is to select the best path for the network, the trust inconsistency needs to be minimized.

The inconsistency in DSR-F is 6.5% smaller than that of AODV-F and less than 7% in DSDV-F. The total efficacy of the recommended confidence is known as the network efficiency.

Each relay node in the second stage is computed based on the trust levels in order to determine which relays may be used for first stage routing and to select the appropriate data transfer path.

The proposed Fuzzy-based Trust model functions well in conjunction with the DSDV Protocol to demonstrate the efficacy and reliability of the suggested system.

DIS is recommended as a means of detecting wrongdoing in order to prevent entities inside the vehicle network from disseminating false information.

5. CONCLUSION

A vehicle routing model was developed, with a focus on travel, QoS, accidents, and traffic. The fuzzy deduction technique was used to develop the QoS-based cost function.

The routing model was solved using LA, and the computation time's cost and convergence were determined. The results of L AG may be shown by utilizing well-known tests like convergence analysis, complexity analysis, and cost analysis to compare the results with GA.

The testing findings indicate that the computation time of LA is almost 72% faster than that of GA. In particular, LA has a high convergence rate (2.2 percent GA difference) and reduces the expenses associated with collision, congestion, and quality of service (QoS) when used. The findings show that LA considerably lowers.

Scalability issues, costly redundancy, an inability to quickly adjust to topological changes, excessive latency, and other issues are some of the issues that VANET's research focuses on.

In order to determine the best course of action with the highest probability, lowest latency, and maximum packet delivery ratio, this thesis provides adaptive routing protocols for urban environments.

We consider routing difficulties to be a combination of non-linear optimization problems in these protocol routing solutions, and we provide methods based on ACOs.

We first provide the AQRV intersection-based routing protocol, which combines proactive and reactive elements to create and maintain the best possible Quality of Service route from source to destination. Because of the ACO's capabilities, several forwarders can collaborate closely to identify routes that are available to candidates.

To anticipate vehicle locations and mitigate certain VANET dangers, a multi-layer learning model might eventually be created. Every model demonstrated that compared to the group, the predictive model had a much greater influence communications incidents could be avoided.

6. FUTURE WORK:

Vehicle ad hoc networks were viewed as fascinating and promising fields for further study in wireless networking and communications by many experts.

However, there remain numerous obstacles in this field that must be addressed and overcome.

Finding answers for problems with channel congestion, storm avoidance, and messaging to target vehicles in VANET are the main priorities at the moment.

Future study might focus on developing a privacy approach for non-safe apps that strikes a balance between user privacy and service quality.

The methods used for real-time modeling, hosting, and functioning of automobiles, vehicle communications networks, and user privacy identifiers may be investigated.

By using the ad-hoc automobile network as a middleware platform for online patient monitoring of mobile patients or vehicle users, the V health system is proposed. The V-Health system keeps an eye on vehicle users' emergencies when using VANETs.

ACKNOWLEDGMENTS

Thanks, Sachin & Vibhuti for your consistent support during my work.

REFERENCES

1. Zhengming Li, Congyi Liu & Chunxiao Chigan 2013, ‘On Secure VANET-Based Ad Dissemination With Pragmatic Cost and Effect Control’, IEEE Transactions on Intelligent Transportation Systems, vol. 14, no. 1, pp. 124-30.

2. Sabet, Mehrdad, Reza A Zoroofi, Khosro Sadeghniiat-Haghighi & Maryam Sabbaghian 2012, ‘A new system for driver drowsiness and distraction detection’, IEEE 20th Iranian Conference on Electrical Engineering (ICEE), pp. 1247-1251.

3. Saif Al-Sultan, Ali H Al-Bayatti & Hussein Zedan 2013, ‘Context aware driver behavior detection system in intelligent transportation systems’, IEEE Transactions on Vehicular Technology, vol. 62, no. 9, pp. 4264-4275.

4. Sumit Khandelwal, A, Ashwini B Abhale & Uma Nagaraj 2014, “Accident prevention and air pollution control using VANET under cloud environment”, In Proceedings of 3rd International Conference on

5. Wen Yao, Huijing Zhao, Franck Davoine & Hongbin Zha 2012, 'Learning lane change trajectories from on-road driving data' In Intelligent Vehicles Symposium (IV), pp. 885-890.

6. Surmukh Singh, Sunil Agrawal, "VANET Routing Protocols: Issues and Challenges", Proceedings of 2014 RAECS UIET Panjab University Chandigarh, 06 – 08 March, 2014 978-1-4799-2291-8/14/$31.00 ©2014 IEEE, pp 205-210.

7. Komal Mehta, Dr. L. G. Malik, Dr. Preeti Bajaj, "VANET: Challenges, Issues and Solutions", 2013 Sixth International Conference on Emerging Trends in Engineering and Technology 978-1-4799-2560- 5/13 $31.00 © 2013 IEEE DOI 10.1109/ICETET.2013.18, pp 64-66.

8. Sandeep Kumar Arora," A Comprehensive Review on Routing in VANET," International Journal of Grid and Distributed Computing Vol. 9, No. 10 (2016), pp.375-384

9. Rakesh Kumar 2012," A Comparative Study of Various Routing Protocols in VANET," IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 4, No 1, July 2011 ISSN (Online): 1694-0814

10. Julia Silva Webe 2021," VANET simulators: an updated review," *Journal of the Brazilian Computer Society* **volume 27**, Article number: 8 (2021)

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Researcher, Dr Pallavi Sachin Patil has five years of industrial experience in addition to over twelve years of teaching experience. I graduated from Savitribai Phule Pune University in Jalagaon with a master's degree in computer engineering and a bachelor's degree in information technology from North Maharashtra University. Twenty of my articles have been presented at conferences and published in national and international journals, proving how motivated and passionate I am about teaching. Ad hoc networks are my field of interest. My goal is to carry out additional research into the development of road safety applications that can save lives and human hours by using VANET applications to increase driver attentiveness. Thank you for viewing my work.