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Intelligent Opportunistic Routing in VANETs using Neural Network

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ABSTRACT

Several research areas attract researchers in the field of Vehicular Ad Hoc Networks (VANETs), a network recognized for its constraints and challenges, particularly in routing. Ensuring efficient routing is challenging due to network changes and frequent link interruptions. These days, Artificial Intelligence (AI) is the technology that is growing the fastest and changing the most. As a result, their technological advancements have had a significant impact on the development of routing protocols. Our goal in this paper is to incorporate AI-based methods to improve the performance of routing in VANET, especially Opportunistic Routing (OR), which is very intriguing. For this, we chose the Fuzzy Logic Opportunistic Routing protocol (FLOR), which uses fuzzy logic. After conducting a thorough analysis of this protocol, we have identified specific drawbacks and limitations. To address these issues, we will integrate AI techniques to create an adaptive and intelligent routing protocol that leverages a neural network. This combination of these two approaches will ensure better performance in terms of packet delivery and throughput and will reduce packet loss.

Keywords: VANET, Opportunistic Routing, FLOR Protocol, Fuzzy Logic, Artificial Intelligence, Quality of Service, Neural Network.

I. INTRODUCTION

Vehicular Ad hoc Networks (VANET) are known for their rather special characteristics such as dynamic topology, short-duration communication link (Satyanarayana & Selvakumar, 2023), such characteristics make routing complex, more precisely routing with Quality of Service (QoS), where the network must prove a certain level of service to its users by ensuring better reliability, high throughput and low latency, to meet such requirements, classical routing cannot be a solution. On the other hand, Opportunistic Routing (OR) gives better results by multiplying the choice of optimal paths and minimizing packet loss (Jakubiak & Koucheryavy, 2008), particularly protocols that use fuzzy logic, like FLOR (Azimi Kashani, Ghanbari & Rahmani, 2020). To decide whether to rebroadcast, FLOR considers three important factors: the number of duplicated packets, local density, and packet progress. Then, these three parameters are utilized as the input of the fuzzy logic system. FLOR performs better than conventional flooding and probabilistic procedures, but its wider use is limited by several issues. This protocol uses a static fuzzy rules set which presents a lack of adaptability to different network conditions, then, the three parameters are not enough to decide if the node is the best or not for rebroadcasting, another observation in this context is the lack of consideration for the condition of the links between vehicles, which can lead to significant packet losses, given that a primary characteristic of VANET networks is the instability of these links. To address these challenges and create an intelligent and dynamic routing protocol, we believe that integrating an Artificial Intelligence (AI) method is essential. This integration will improve the protocol's ability to adapt to changing network conditions and optimize performance in real-time. Among the methods of AI that has made great success in predictions and solving complex problems, we have neural network (Mohamed, 2023; Rodriguez, 2022).

In this paper, we propose an improvement of the FLOR protocol using Neural Networks (NN-FLOR). The rest of this article is as follows: In Section II, the proposed innovation is described. Section III describes the methods used and introduces the model of the neural network. We also discuss the limitations of our work in Section IV. Finally, Section V makes a conclusion and future work.

II. SOME ROUTING CONTRIBUTIONS IN VANETS

Recent studies have increasingly focused on integrating AI into routing protocols to enhance QoS in VANETs. Various learning models have been explored to address the network's dynamic topology, high mobility, and link instability. For instance, (Bagirathan, Saravanan, Vijayabhaskar, & Sivasankar, 2025) proposed an Ensemble LSTM-driven secure routing protocol combining trust evaluation and coati optimization, achieving significant improvements in packet delivery ratio and delay reduction. Similarly, (Bennaoui, Guezouri, & Keche, 2024) leveraged a Deep Neural Network (DNN) for data dissemination, improving message coverage and delivery efficiency through intelligent forwarding path prediction. (Muktar, Fono, & Zongo, 2023) introduced an Artificial Neural Network (ANN) model to predict signal degradation caused by urban obstacles, enabling routing through paths with minimal Bit Error Rate (BER). Other works explored hybrid intelligent approaches for dynamic routing and security enhancement. (Bi, Huang, Zhang, Chen, & Lyu, 2025) combined Graph Neural Networks (GNN) with Deep Reinforcement Learning (DRL) to construct adaptive, topology-aware routing strategies that outperform classical algorithms in end-to-end delay and reliability. Similarly, (Ul Hassan et al., 2024) developed an ANN-based secure routing mechanism within an enhanced AODV framework to mitigate black hole attacks, while (Kate et al., 2025) proposed a Discrete Hopfield Neural Network (DHNN) optimized with metaheuristic techniques for robust malicious node detection and secure communication. Despite these advancements, most existing solutions remain limited by their dependency on centralized learning, high computational

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costs, or narrow QoS optimization scope often focusing on a single metric such as delay or reliability. Our work differs by proposing an adaptive AI-based routing protocol that dynamically balances multiple QoS parameters while maintaining scalability under dense and highly mobile VANET conditions. By combining intelligent decision-making with real-time environmental perception, our approach positions itself as a next-generation solution toward fully autonomous, QoS-aware vehicular communication systems.

III. PROPOSED INNOVATION

The OR is very interesting for VANET, considering multiple candidates for retransmission allows network to reduce packet loss and ensuring packet delivery, but the use of classic routing with simple approaches does not meet our expectations in terms of QoS, especially with the routing difficulties in VANET. For this, we studied the FLOR protocol, which is an OR protocol that uses fuzzy logic. Our choice of this protocol is based on two criteria: first, it is an OR protocol; second, it uses fuzzy logic, which is an AI method but does not use learning. Fuzzy logic is used to solve problems where information is uncertain or lacking in precision and decision-making is complicated (Qayyum, Birjis, & Bourouis, 2020).

To improve this protocol, we propose the NN-FLOR protocol, an efficient VANET routing approach that uses both fuzzy logic and neural networks. The proposed routing logic concentrates on Vehicle-to-Vehicle communication (V2V).

In the FLOR protocol, the retransmission of the packet is done based on the decision obtained by the fuzzy logic system where several candidates from the group could carry out the rebroadcasting operation, but this group can contain nodes without any efficiency and advantage of sending them the packets, for this and before trying to retransmit or not the packet, we will develop a neural network in each node, which will give us the best nodes to retransmit the packet, and these nodes will be the intended receivers that define the broadcast zone.

In general, three primary processes comprise the opportunistic routing operation:

- Selection of the collection of rebroadcasting candidates.

- Data multi-casting to the candidate rebroadcasters.

- Data transmission (Azimi, ghanbari, & Rahmani, 2020).

So, our innovation focuses on selecting the set of rebroadcasting nodes using a neural network. After this selection, we maintain the FLOR protocol as it is.

IV. METHODS

In this section, we provide the fundamental methods and tools utilized in our proposed innovation

A. *Fuzzy logic*

Fuzzy logic is similar to human logic, it encompasses the set of options between the numeric values yes and no, which gives the possibility to deal with uncertain and unreliable information where decision making is very delicate (Li & Yao, 2023), for this reason, fuzzy logic is considered as an excellent choice for many control system applications (Bariket, & Padhi, 2020). The FLOR protocol uses three criteria to optimize the relay node selection : packet advancement (distance from the node to one of its rebroadcast candidates), local density (number of nearby vehicles), and amount of duplicated packets (prevent redundancy and minimize collisions). These parameters are the input of the fuzzy logic rebroadcast system. In this system, three steps are followed to make a set of rules: fuzzification, fuzzy inference, and defuzzification. By using these twenty-seven rules together, a fuzzy output is obtained that indicates whether to rebroadcast or not..

B. *Neural network*

NN models, also known as Artificial Neural Networks (ANNs), are usually made up of layers, simple nonlinear functions, stacked one on top of the other (Chen, Rajib, & Choi, 2021).

To effectively perform our work, we begin by acquiring our dataset, as this is the crucial first step in developing a model; we start with data collection, processing and arranging it properly according to the ML model requirements (Cardenas, 2021; Dongare, Kharde, & Kachare, 2012).

Our data set contains five metrics: distance, vehicle's direction, relative velocity, vehicle density and latency:

- **Distance**: can be calculated from each neighbor or candidate node C to the packet destination D as Eq. 1.

$$\text{Distance} = \sqrt{(x_c - x_D)^2 + (y_c - y_D)^2} \quad (1)$$

- **Vehicle direction:** It provides information on the direction of travel to the destination, calculated for each neighborhood candidate node to be the subsequent forwarding vehicle.
- **Relative Velocity**: The third parameter is the relative velocity between the neighbor node and the source node or the current node, which can be calculated as Eq. 2.

$$V_{si} = |V_s - V_i| \quad (2)$$

- **Vehicle density:** It is the number of neighbors that each candidate for the next forwarding vehicle has within the transmission range**.**
- **Latency:** The duration of data transfer from a source to a destination. It shows how long it takes a data packet to move across a network and get to its destination.

These five metrics are the inputs of our neural networks called features, and the output of the model is the probability of the successful delivery of a packet, which represents the labeled data, as shown in Tab. 1.

After the collection of data, the next step is to train NN classification algorithms and evaluate them through the usual machine learning performance metrics (Levander, 2021). Finally, we implement this model in our proposal routing protocol which will be evaluated with a simulator framework.

The general architecture of our approach is as described in Fig. 1. It's a hybrid approach that combines fuzzy logic and neural network.

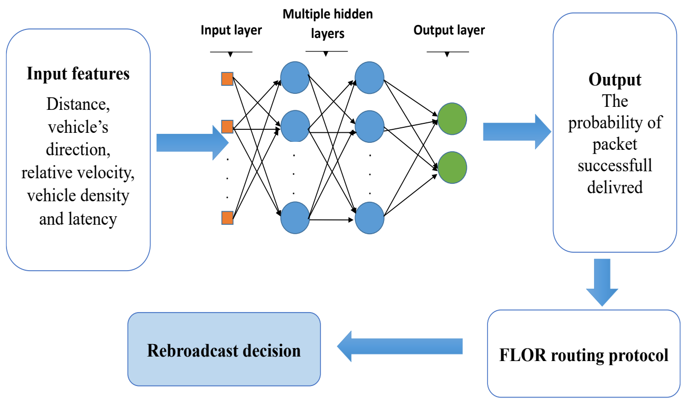

Fig. 1. The general architecture of NN-FLOR

TABLE I. DATA COLLECTION EXAMPLE

Sample	*idPacket*	*X_1 Distance*	*X_2 Vehicle direction*	*X_3 Relative velocity*	*X4 Vehicle density*	*X_5 Latency*
1	1	$X_{1,1}$	$X_{2,1}$	$X_{3,1}$	$X_{4,1}$	$X_{5,1}$
2	1	$X_{1,2}$	$X_{2,2}$	$X_{3,2}$	$X_{4,2}$	$X_{5,2}$
3	1	$X_{1,3}$	$X_{2,3}$	$X_{3,3}$	$X_{4,3}$	$X_{5,3}$
4	1	$X_{1,4}$	$X_{2,4}$	$X_{3,4}$	$X_{4,4}$	$X_{5,4}$
5	1	$X_{1,5}$	$X_{2,5}$	$X_{3,5}$	$X_{4,5}$	$X_{5,5}$

V. LIMITATIONS

- Neural networks necessitate large datasets for reliability, posing challenges in distributed environments such as VANET.
- High processing time: Deep neural networks (DNN) in particular demand a lot of processing power, which is hard to supply in cars with little capacity.
- Quick Decision required: VANET routing must be completed in milliseconds. However, unacceptably high latency can be introduced by a sophisticated neural network.

VI. FUTURE WORK

QoS routing in VANETs has continued to attract the attention of many researchers and remains a significant challenge to overcome. With the great success of AI techniques in solving various complex problems in several domains, the integration of AI into routing in VANETs has become a promising approach. This article is a work in progress that presents concepts that will be expanded upon in our subsequent work. As future work, we will deepen our approach, train the neural networks with a large amount of data to have a better prediction model, validate our approach by simulation under NS3 and measure its performance in terms of QoS, by calculating the different metrics, a final phase will be to compare this approach to other routing protocols such as FLOR and FEZZBER.

REFERENCES

Satyanarayana, R. K., & Selvakumar, K. (2023). *Bi-linear mapping integrated machine learning based authentication routing protocol for improving quality of service in vehicular Ad-Hoc network. E-Prime - Advances in Electrical Engineering, Electronics and Energy*, *4*, 100145. https://doi.org/10.1016/j.prime.2023.100145

Jakubiak, J., & Koucheryavy, Y. (2008). *State of the Art and Research Challenges for VANETs*. https://doi.org/10.1109/ccnc08.2007.212

Azimi Kashani, A., ghanbari, M., & Rahmani, A. M. (2020). *Improving Performance of Opportunistic Routing Protocol using Fuzzy Logic for Vehicular Ad-hoc Networks in Highways*. *Journal of AI and Data Mining*, *Online First*. https://doi.org/10.22044/jadm.2020.8605.1997

Mohamed, K. S. (2023). *Deep learning-powered technologies: Autonomous driving, artificial intelligence of things (AIoT), augmented reality, 5G communications and beyond*. Springer Nature Switzerland AG. https://doi.org/10.1007/978-3-031-35737-4

Rodriguez, A. (2022). *Deep learning systems: Algorithms, compilers, and processors for large-scale production*. Springer Nature Switzerland AG. https://doi.org/10.1007/978-3-031-01769-8

Bagirathan, K., Saravanan, N., Vijayabhaskar, K., & Sivasankar, C. (2025). An intelligent recurrent neural network driven secured routing protocol for vehicular ad hoc networks. *Knowledge-Based Systems, 317*, 113371. https://doi.org/10.1016/j.knosys.2025.113371

Bennaoui, A., Guezouri, M., & Keche, M. (2024). Improving VANET data dissemination efficiency with deep neural networks. *Journal of Network and Systems Management, 32* (1), 81. https://doi.org/10.1007/s10922-024-09858-0

Muktar, B., Fono, V., & Zongo, M. (2023). Predictive Modeling of Signal Degradation in Urban VANETs Using Artificial Neural Networks. *Electronics, 12(18), 3928*. https://doi.org/10.3390/electronics12183928

Bi, X., Huang, L., Zhang, B., Chen, Z., & Lyu, Z. (2025). A dynamic routing algorithm for VANET with graph neural networks and deep reinforcement learning. *International Journal of Sensor Networks, 47*(2), 119–134. https://doi.org/10.1504/IJSNET.2025.146775

Ul Hassan, M., Al-Awady, A. A., Ali, A., Sifatullah, Akram, M., Iqbal, M. M., Khan, J., & Abdelrahman Ali, Y. A. (2024). ANN-based intelligent secure routing protocol in vehicular ad hoc networks (VANETs) using enhanced AODV. *Sensors, 24*(3), 818. https://doi.org/10.3390/s24030818

Kate, C., Tudigani, A., Raghavendra, S., Lizy, A., Malathi, M., & Johari, L. (2025). Discrete Hopfield neural network model for secure electrical routing in VANETs to avoid blackhole attacks. *Proceedings of the 2025 International Conference on Intelligent Computing and Control Systems (ICICCS),* 630–636. https://doi.org/10.1109/ICICCS65191.2025.10984526

Qayyum, E., Birjis, H., & Bourouis, S. (2020). Smart fuzzy logic-based density and distribution adaptive scheme for efficient data dissemination in vehicular ad hoc networks. Electronics, 9(8), 1297. https://doi.org/10.3390/electronics9081297

Li, L., & Yao, L. (2023). *Fault-tolerant control of fuzzy stochastic distribution systems with packet dropout and time delay*. IEEE Transactions on Automation Science and Engineering. https://doi.org/10.1109/TASE.2023.3266065

Bariket, P., & Padhi, D. K. (2020). *An overview of AI techniques and their applications*. Journal of Nonlinear Analysis and Optimization, 11, n° 1.

Chen, J., Rajib, P., & Choi, Y.-J. (2021). an Efficient Neural Network-Based Next -Hop Selection Strategy for Multi-hop VANETs. *2021 International Conference on Information Networking (ICOIN)*, 699-702. https://doi.org/10.1109/icoin50884.2021.9333974

Cardenas, L. L., Mezher, A. M., Barbecho Bautista, P. A., Astudillo Leon, J. P., & Igartua, M. A. (2021). *A Multimetric Predictive ANN-Based Routing Protocol for Vehicular Ad Hoc Networks*. *IEEE Access*, *9*, 86037-86053. https://doi.org/10.1109/ACCESS.2021.3088474

Dongare, A., Kharde, R., & Kachare, A. D. (2012). Introduction to artificial neural network. *International Journal of Engineering and Innovative Technology* (IJEIT), 2(1), 189–194.

Levander, B. (2021). Machine learning book: Learn machine learning, deep learning, data science, and more! : Machine learning beginners. Independently Published.