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Intelligent Backoff Management Scheme Applying Adaptive Neuro-Fuzzy Inference System in Vehicular Ad-hoc Networks

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***Abstract*—Intelligent Transportation Systems rely heavily on the Vehicular Ad-hoc Network to enhance road safety and comfort. This research proposes and evaluates an intelligent backoff management scheme, utilizing Adaptive Neuro-Fuzzy Inference System (ANFIS), for the Vehicular Ad-hoc Networks. The proposed scheme is trained by TensorFlow to adjust the contention window size at the MAC layer of IEEE 802.11p. Taking into account the local density, local spatial distribution, and successful/unsuccessful transmission records, each transmitting node can determine the best contention window value for transmitting packets. This scheme effectively mitigates packet collisions, ensuring a high packet delivery ratio and average throughput, along with a low average end-to-end delay for various network scenarios. Simulation results confirm the efficiency of the proposed scheme and also show that it outperforms the conventional IEEE 802.11p method and other recent protocols.**

***Index Terms*—Vehicular Ad-hoc Networks, backoff management, contention window, ANFIS, TensorFlow, IEEE 802.11p.**

I. Introduction

Vehicular Ad-hoc Network (VANET) is a subclass of Mobile Ad-hoc Network (MANET), which enables vehicle-to-vehicle communications on the roads. Since VANETs support many safety and comfort applications, the design and enhancement of VANET communication protocols are crucial. However, the constantly rapid changing nature of VANETs makes the design of reliable VANET communication solutions a complex task.

Wireless Access in Vehicular Environments (WAVE) [1], introduces IEEE 802.11p as the amendment of the IEEE 802.11 standard for the PHY and MAC layers, in addition to the IEEE 1609 family of standards for the upper layers. According to the IEEE 802.11p Distributed Coordination Function (DCF), each transmitting node senses the wireless medium to determine whether the channel is idle or not. If the transmitting node finds the channel idle for longer than Arbitration Inter-Frame Space (AIFS) it immediately transmits, otherwise, it needs to wait until the channel becomes idle. After that, there is an additional waiting time (backoff) which is a randomly selected number of time slots from the interval $[0, CW]$, where CW is the contention window size. Depending on the access category, the value of CW is defined by CW_{min} and CW_{max}. When two or more transmitting nodes pick the same backoff time, packet collisions will happen. A larger contention window size can mitigate packet collisions because it decreases the probability that two or multiple nodes select the same backoff value. However, the larger contention window potentially increases the delay. Therefore, an adaptive backoff process is used to determine an optimal CW level, taking into account the current network situation. In dense networks with a larger number of transmitting nodes, a larger contention window size can improve the packet delivery ratio. Conversely, in sparse networks with a smaller number of transmitting nodes, a smaller contention window size can be beneficial, leading to reduced delays.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a computational model which combines the capabilities of adaptive control systems, artificial neural networks (ANNs) and fuzzy logic to perform data analysis, pattern recognition, and decision-making tasks [2]. ANFIS is an effective method to model and control complex systems, especially when the underlying relationships between variables are not well-defined [3]. ANFIS has both numerical and linguistic knowledge. This makes ANFIS more observable to the users in comparison with artificial neural networks [4]. The ability of ANFIS to handle uncertain and imprecise information makes it particularly useful in VANETs system designs.

In order to propose a dynamic and adaptive backoff scheme, we introduce a hybrid historical and data processing-oriented contention window size adjustment model based on an Adaptive Neuro-Fuzzy Inference System. To the best of our knowledge, there is currently no ANFIS-based model proposed to enhance the backoff process and to adjust the contention window size in vehicular ad-hoc networks. The contributions of this work are as follows:

- We propose an ANFIS-based backoff management scheme to adjust the contention window size in vehicular ad-hoc networks taking into consideration the local density, spatial distribution and history record of previous transmissions. To the best of our knowledge,

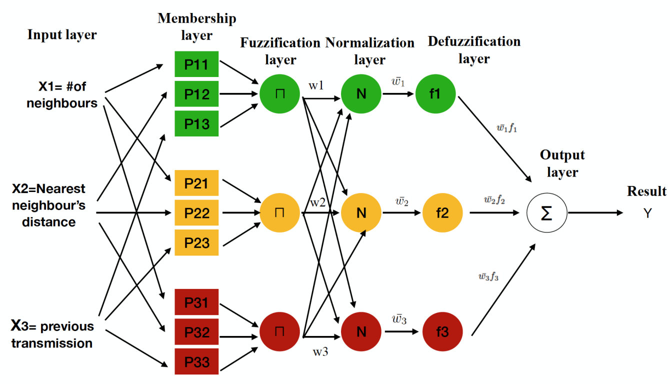

Fig. 1: ANFIS model design

no other protocol takes into account all these factors in combination.

- In order to train the ANFIS model, we use ns-3 and SUMO to generate the dataset including the information about each transmitting node's number of neighbors (local density), distance to its nearest neighbor (spatial distribution), and record of the previous transmissions and contention window sizes.
- TensorFlow is applied to optimize the ANFIS parameters and train the model.
- To evaluate the overall performance of the proposed scheme, the results of ANFIS training are used in ns-3 network simulations. The simulation results have demonstrated that our proposed ANFIS-based scheme outperforms other existing protocols in the literature in terms of packet delivery ratio, average throughput and average end-to-end delay.

The rest of this paper is organized as follows: Section II provides a literature review on contention window size adjustment methods proposed for the IEEE 802.11 family of standards. Section III describes our proposed scheme. Section IV presents simulation results. Finally, in Section V, we conclude the paper.

II. Related Work

In this section, backoff solutions in terms of contention window size adjustment introduced for the IEEE 802.11p standard are described.

In [5], a cross-layer multi-hop broadcast protocol for vehicular ad-hoc networks is proposed. At the MAC layer, a Q-learning algorithm is introduced to adjust the size of contention window where the agents receive the rewards according to their previous transmission record. The network simulator ns-2 is used to simulate the network environment and train the Q-learning algorithm.

The proposed method in [6] is a partitioning-based CW adjustment approach for VANETs. Vehicles in the farthest partition from the sender use a smaller contention window.

The proposed method in [7] deploys a Q-learning technique for the backoff process of channel access in IEEE 802.11p networks. Considering vehicles in the network as the agents, the proposed Q-learning algorithm adjusts the contention window for a hybrid backoff process in which linear and exponential backoff are combined. The authors use the network simulator ns-3 to simulate an IEEE 802.11p-based network and conduct 3000 transmissions per episode to train the Q-learning-based backoff process.

In order to improve the backoff time selection performance in IEEE 802.11p, [8] introduces the F-802.11p scheme. F-802.11p is a fuzzy model which controls broadcast of the Wave Short Messages (WSMs), Wave Service Advertisement (WSA) messages, and Basic Safety Messages (BSMs) and reduces the number of beacon messages to use the available bandwidth more effectively. The results are obtained by using the OMNeT++ simulator, SUMO, the Veins framework for V2X, and MATLAB fuzzy toolbox.

In [9], a radial basis function neural network is utilized to modify the enhanced distributed channel access (EDCA) backoff to ensure that urgent safety messages are successfully disseminated through the network. This system uses the information about the message priority, the sensitivity of the road, the threshold of the buffer, and the type of vehicle. The authors use the ns-2 network simulator and SUMO to generate the neural network input data and evaluate the performance of the proposed backoff process.

In [10], the authors propose a dynamic CW selection model for the IEEE 802.11p MAC layer. This model uses a fuzzy logic system to determine the size of CW by taking density, velocity, and link quality factors into consideration.

The authors in [11] propose a contention window size adjustment method for IEEE 802.11p-based Internet of Vehicles (IoV) networks. The method takes the number of neighbors into consideration and applies a Q-learning algorithm to control the size of contention windows. The veins simulation platform is used to simulate the network environment and conduct the learning process of CW adjustment method.

None of these discussed CW adjustment protocols simultaneously use the information about network density, spatial distribution, and transmission records to adapt the backoff process.

Our proposed scheme, described in the next section, integrates all of this information to improve the performance.

III. Proposed Scheme

In this section, we present our proposed Adaptive Neuro-Fuzzy Inference System-assisted backoff management scheme for Vehicular Ad-hoc Networks. VANETs have a constantly changing pattern of network density and distribution which is due to the fast movement of vehicles. Therefore, the backoff management solution should intelligently track the situation. Our proposed backoff management is implemented through adaptive contention window adjustment. With a large number of transmitting nodes, the MAC should have a relatively large contention window size to prevent unnecessary packet collisions. On the other hand, a small contention window size results in a shorter delay when the number of nodes trying to access the channel is small. In order to estimate the number of transmitting nodes, the local density and spatial distribution of nodes are considered determining factors. Our scheme also uses the transmission records (successful or unsuccessful) of nodes to track an optimum value of contention window size in different environment and traffic scenarios.

A. System Premises

In our proposed scheme, it is assumed that all data exchanging and communications are secured according to the IEEE 1609.2 standard. Each node (vehicle) is able to determine its position using a Global Positioning System (GPS). Also, it is assumed that all the nodes in the network are aware of the average communication transmission range. Nodes periodically exchange beacon messages with their neighbors and update their neighboring tables accordingly. A basic beacon message (with a packet sequence number) contains information about the originator's ID, position, and velocity.

B. Data Acquisition

In order to generate the dataset, ns-3 is used. The IEEE 802.11p-based network is designed to perform multi-hop broadcast data dissemination via the network. When a node receives a new broadcast message it decides whether to retransmit the broadcast message or drop it by comparing the value of the calculated spatial distance-to-mean with a dynamic threshold [12]. The calculation is done based on the information exchanged via beacon messages. Each transmitting/re-transmitting node determines its number of neighbors, and nearest neighbor's distance. Since in IEEE 802.11p a broadcast MAC frame acknowledgement is not considered, the transmitting node sets a timer and waits for a t_{ack} time:

$$t_{ack} = 0.1 * (\frac{R-d}{R}) \tag{1}$$

where R denotes the average communication transmission range and d is the nearest neighbor's distance. If during this time the node overhears the message from a neighbor, it records the transmission as a success. The dataset is obtained from the simulation of 56 scenarios, where the number of nodes in the network is 20, 30, 40, 50, 100, 150, 200, 400 and the value of CW_{min} is considered to be 15, 31, 63, 127, 255, 511, and 1023. After performing the data pre-processing steps, the dataset is used to train the ANFIS model to predict the optimal CW_{min} in different scenarios.

C. ANFIS Model

Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the adaptive abilities and learning of neural networks with the human-like reasoning and linguistic interpretation provided by fuzzy logic. ANFIS uses a hybrid learning algorithm to tune the parameters of a fuzzy inference system based on input-output data.

In this paper, we train the fuzzy inference system based on the generated dataset of inputs and output. The system is fed by three input variables (number of neighbors, nearest neighbor's distance, previous transmission) and one output (CW_{min}).

Considering a first-order Takagi–Sugeno fuzzy system [13], the set of fuzzy $If - Then$ rules for our system with one output, z, and three input (x_1, x_2 and x_3) parameters is described as follows:

Rule 1: If x_1 is A_1 and x_2 is B_1 and x_3 is C_1 then
$z_1 = p_1x_1 + q_1x_2 + r_1x_3 + s_1$

Rule 2: If x_1 is A_2 and x_2 is B_2 and x_3 is C_2 then
$z_2 = p_2x_1 + q_2x_2 + r_2x_3 + s_2$

Rule 3: If x_1 is A_3 and x_2 is B_3 and x_3 is C_3 then
$z_3 = p_3x_1 + q_3x_2 + r_3x_3 + s_3$

where A_i, B_i, and C_i are linguistic values of membership functions defined by fuzzy sets and p_i, q_i, r_i and s_i denote consequent parameters of fuzzy $If - Then$ rules.

As shown in Fig. 1, the structure of the ANFIS model consists of five layers with different function types to generate the target value as a combination of input variables.

1) Fuzzification Layer: This layer converts the crisp input values into fuzzy sets using membership functions. The output of each node in this layer is a degree of membership, which is a value between 0 and 1. In our ANFIS model we apply the Gaussian membership function to represent the degree of membership:

$$\mu(x) = e^{-0.5(\frac{x-c}{\sigma})^2} \tag{2}$$

where c is the position of the center of the peak, and σ is the standard deviation. Both c and σ are adjustable parameters of the membership function. In Section IV, we show how a Gaussian function outperforms other functions used in our ANFIS model.

2) Production Layer: The Production layer has a fixed node function, and the output of this layer is the firing strength of the associated fuzzy rule, w_i, which is calculated by multiplying all incoming signals:

$$w_i = \prod_i \mu_i = \mu_{A_i}(x) * \mu_{B_i}(x) * \mu_{C_i}(x), \quad i = 1,2,3. \tag{3}$$

where μ_{A_i}, μ_{B_i}, and μ_{C_i} represent the membership functions.

3) Normalization Layer: The Normalization layer has a fixed node function, where the output of this layer is the normalized firing strength, $\bar{w}_i$, which is given by:

$$\bar{w}_i = \frac{w_i}{\Sigma_i w_i}, \quad i = 1,2,3. \tag{4}$$

4) Defuzzification Layer: Layer 4 or the defuzzification layer consists of adaptive nodes to aggregate the fuzzy outputs from the previous layer and convert them to the crisp output value.

$$\bar{w}_i z_i = \frac{w_i}{\Sigma_i w_i}(p_i x_1 + q_i x_2 + r_i x_3 + s_i), \quad i = 1,2,3. \tag{5}$$

5) Output Layer: The output layer has a single fixed node, which calculates the final output of the ANFIS model by summation of all incoming signals from the defuzzification layer.

$$z = \Sigma_i \bar{w}_i z_i, \quad i = 1, 2, 3. \tag{6}$$

The learning process of ANFIS includes adapting the parameters of the membership functions and rules of the fuzzy inference system. ANFIS uses a combination of gradient descent and backpropagation techniques to complete the learning process by minimizing the error between the actual output and the desired output. We use Adaptive Moment Estimation (ADAM) optimizer to train the ANFIS network. ADAM is an advanced gradient descent optimization model which adjusts the learning rate of each parameter according to their past gradients and magnitudes. The main reason we choose ADAM is its ability to provide a fast convergence speed and an effective performance compared with other adaptive learning rate algorithms [14]. Based on the gradient descent algorithm, the parameter updating equation is:

$$\theta = \theta - \epsilon . g \tag{7}$$

where g denotes the gradient of the cost function with respect to θ, and where ϵ is the learning rate.

The ADAM optimization iteration is described by:

$$\theta = \theta - \epsilon . \frac{[\beta_1 . m_{t-1} + (1-\beta_1). g_t]/(1-\beta_1^t)}{\sqrt{[\beta_2 . v_{t-1} + (1-\beta_2). g_T^2]/(1-\beta_2^t)} - \epsilon} \tag{8}$$

where β_1 and β_2 denote the exponential decay rates, m_i and v_i are the $1st$ and the $2nd$ moment vectors in the tth epoch.

D. CW Adjustment

Our proposed ANFIS-based backoff scheme is trained to adjust the contention window size. Based on the proposed system, each transmitting node updates its contention window size by considering its number of neighbors (local density), the nearest neighbor's distance (local spatial distribution), and whether the previous transmission (with the current size of CW_{min}) was successful or not. As mentioned earlier, according to the IEEE 802.11p standard, the value of CW_{min} is defined to be in the set of $\{15, 31, 63, 123, 255, 511, 1023\}$. Therefore, the transmitting node updates the size of contention window, by keeping, increasing, or decreasing the value of its current CW_{min}. Equation (9) indicates the update of the current CW_{min} level:

$$CW_{min_{t+1}} = \begin{cases} CW_{min_t}, & keep \\ \frac{(CW_{min_t} - 1)}{2}, & Decrease \\ (CW_{min_t} * 2) + 1, & Increase \end{cases} \tag{9}$$

We consider the initial value of CW_{min} to be 15.

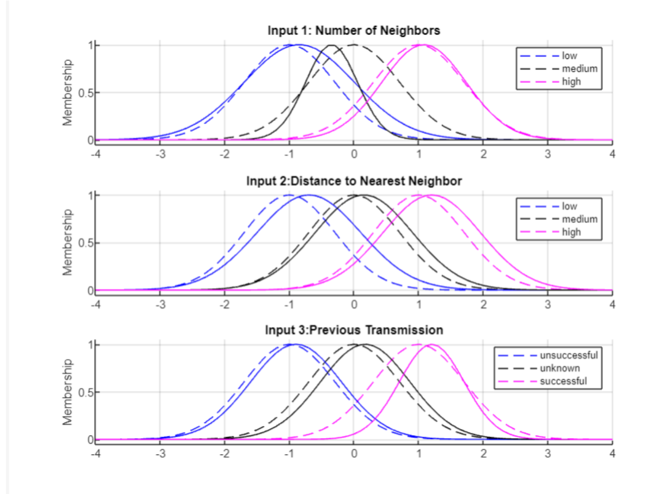

Fig. 2: Trained Membership Functions (solid line) and Initial Membership Functions (dotted line)

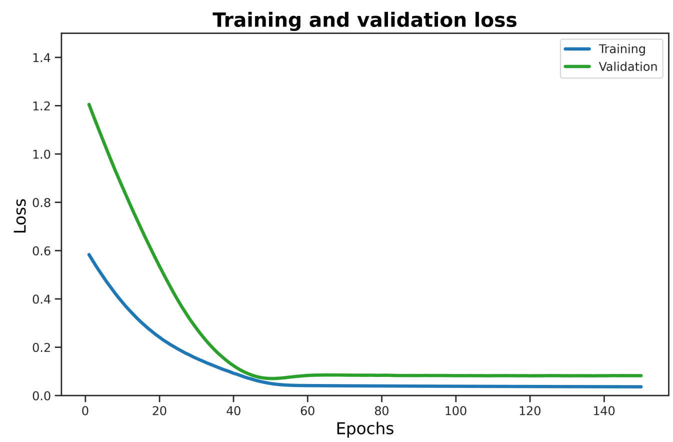

Fig. 3: Training and validation loss over epochs

IV. Performance Evaluation

In this section, similar to [5] - [11], simulations are used to evaluate the performance of the proposed ANFIS-based contention window size adjustment scheme at the MAC layer of vehicular ad-hoc networks (IEEE 802.11p). In order to obtain the results, we use TensorFlow 2.0 to train the ANFIS model, Simulation of Urban MObility (SUMO) to generate mobility traces, and ns-3 to simulate the overall architecture of vehicular ad-hoc networks.

Since our proposed scheme is based on an ANFIS structure (combination of artificial neural networks and fuzzy logic techniques), we utilize the backoff concept at the MAC layer of the protocols Neural-IEEE 802.11p [9], Fuzzy-IEEE 802.11p [10] and compare the efficiency of our proposed scheme with theirs. The proposed Q-learning assisted protocol in [11] is the other protocol that we consider for performance comparison. It yields the best performance so far and can be considered state-of-the-art. These methods are three of the most recent MAC solutions for IEEE 802.11p, and shown to have very good network performance. Additionally, we compare the results with the basic IEEE 802.11p MAC to address how backoff management schemes can improve the efficiency. Three sets of results are presented for each protocol using the following metrics:

- Packet delivery ratio
- Average throughput
- Average end-to-end delay

The results are averaged over five different simulation runs. 95% confidence intervals are calculated and represented using error bars.

A. ANFIS Training with TensorFlow

TensorFlow is an open-source deep learning framework [15]. Python is the recommended programming language for it. We use TensorFlow to build and train our proposed ANFIS system. The dataset is extracted from ns-3 network simulations. To generate the dataset, we consider various network scenarios with different network densities, different values of CW_{min}, and different ranges of speed to capture four parameters: the transmitting node's number of neighbors, the distance between the transmitting node and its nearest neighbor, whether the previous transmission was successful or not, the value of CW_{min} used to transmit. The ANFIS model uses the labeled data, where the first three variables are inputs and the last variable is output. To train the ANFIS model, the ns-3 extracted data with 4398 samples are randomly divided into training and validation sets with the ratio of 0.8 to 0.2. Each input variable has three membership functions. To investigate how the type of membership functions can impact the ANFIS training results, MSE values of each membership function used in ANFIS model are given in Table I. This table shows that the Gaussian function minimizes the MSE.

Fig. 2 depicts the trained Gaussian membership functions for each input and the initial membership functions. Fig. 3 shows the training and validation loss over 150 epochs. The overall trend of the loss curve is declining which indicates that the accuracy of prediction is increasing and verifies the learning process. Also, the validation loss is higher than the loss of the training set.

B. ns-3 Network Simulation Results

The simulations are run using the ns-3.33 network simulator with the parameters summarized in Table II. To simulate the IEEE 802.11p PHY and MAC layers, we employ the WAVE model implemented in ns-3, as the main system architecture for vehicular communications. Nakagami propagation loss model is considered to address the signal strength variation resulted by multipath fading. The simulations are run for a period of 900 seconds.

As mentioned earlier, to generate the mobility traces, we use SUMO [16]. SUMO supports implementations and evaluations of V2X communication technologies by coupling to the network simulator (ns-3 in our work). In this work, a 3x3 Manhattan Grid is used as the urban environment, where the length of each edge is 1km and the distance of any two nearby intersections is 0.5km. These are the steps to generate SUMO traces:

- Step 1: map generation (netgenerate)
- Step 2: random trips generation
- Step 3: routes generation
- Step 4: exporting the traces to ns2mobility output (via ns-3 code)

Using the SUMO car-following model, the speed of each node (vehicle) is adapted to the speed of the leading node. In the simulation, nodes are randomly distributed and routes are randomly generated. Since in vehicular ad-hoc networks, the node density changes with road types and with time, we evaluated the protocols for various numbers of nodes. Simulations are run where the number of vehicles is considered to be 20, 40, 100, 200, and 400.

1) Packet Delivery Ratio: As shown in Fig. 4, in terms of packet delivery ratio, our proposed ANFIS-based CW adjustment scheme outperforms the Fuzzy-based, Neural Network-based, and conventional IEEE 802.11p protocols for all scenarios with different number of nodes. Moreover, our proposed scheme performs slightly better than the QLR-assisted protocol. Since a low CW size can result in packet collisions, in high density networks it is inefficient to consider a low value for the size of CW. Our proposed scheme is trained to efficiently manage the size of CW (based on the local traffic density and spatial distribution), therefore, it shows a higher packet delivery ratio.

2) Average Throughput: Fig. 5 illustrates the average throughput results. We can observe that with the increased number of nodes, the average throughput increases in all protocols. However, our proposed scheme outperform the Fuzzy-based, Neural Network-based, and conventional IEEE 802.11p protocols while it has almost similar results as the QLR-based model. This happens because our proposed scheme is trained based on the record of nodes' previous transmissions, density and distribution of nodes in order to mitigate packet collisions.

3) Average end-to-end delay: Fig. 6 shows the average end-to-end delay for different numbers of nodes. The ANFIS-based scheme provides lower end-to-end delay compared to all the other protocols. The first reason for this is that the protocol incorporates information about local network density, spatial distribution, and previous transmission records. It adjusts the contention window (CW) size by increasing it when the current CW is insufficient and the network experiences numerous collisions. The second reason is that the ANFIS-based scheme considers a smaller value for CW when the collision probability decreases. Therefore, it reduces the waiting time before the transmissions at the MAC queue.

V. Conclusion

We proposed an improved backoff management scheme for the MAC layer of Vehicular Ad-hoc Networks to avoid packet collisions that occur when multiple nodes attempt to transmit packets simultaneously. This adaptive scheme involved adjusting the contention window size based on local density, spatial

TABLE I: MSE of Membership Functions

Membership Function	MSE
Gaussian	0.032
Triangular	0.036
Trapezoidal	0.041
GBell	0.042
Gaussian 2-sides	0.042
Pi-shaped	0.053
Dsigmoidal	0.054
Psigmoidal	0.054

TABLE II: Ns-3 Simulation Parameters

MAC Protocol	IEEE 802.11p
Packet size	200 bytes
Transmission Range	$\sim$ 250 meters
Layer 3 Addressing	IPv4
CW_{min}	15
CW_{max}	1023
Signal Propagation	Nakagami

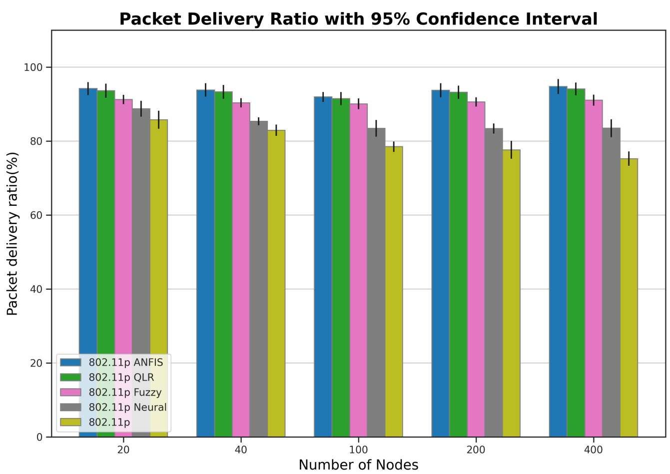

Fig. 4: Packet delivery ratio with respect to number of nodes

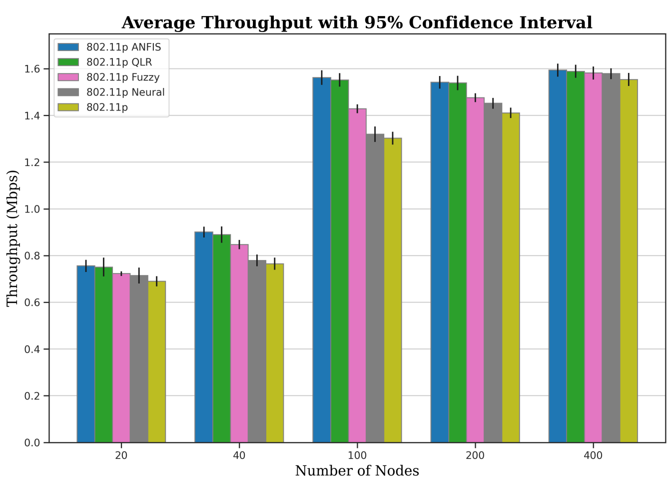

Fig. 5: Average throughput with respect to number of nodes

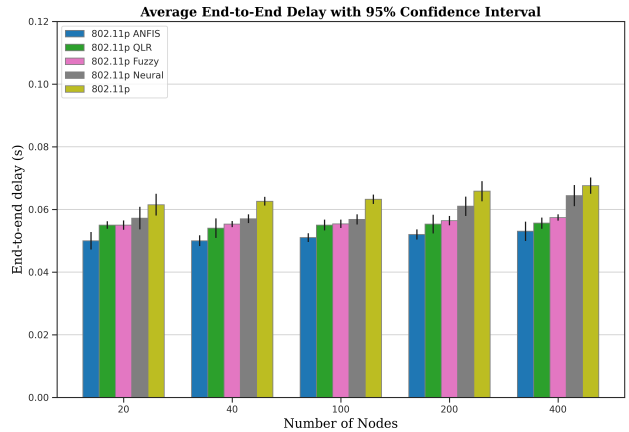

Fig. 6: End-to-end delay with respect to number of nodes

distribution, and successful transmission records. An Adaptive Neuro-Fuzzy Inference System (ANFIS) model trained on these factors was used. Each transmitting node (vehicle) was able to update the contention window size by adjusting the current CW_{min} value. Our simulations demonstrated that this approach resulted in a high packet delivery ratio and low end-to-end delay across a range of node densities, while also providing a high rate of throughput for different density scenarios. The proposed scheme consistently outperforms the basic IEEE 802.11p protocol as well as two recent techniques using a neural network and fuzzy logic, which have been shown to achieve a very good performance. When compared to a Q-learning assisted protocol, our proposed scheme achieves a similar packet delivery ratio and throughput, but it provides the best end-to-end delay across all traffic load densities. Hence, our proposed scheme is an attractive alternative to the other available methods. Furthermore, our simulations have shown that its complexity/simulation time is similar to that of the other approaches. For future work, we plan to apply our scheme to real-world data.

REFERENCES

[1] "Ieee guide for wireless access in vehicular environments (wave) architecture," *IEEE Std 1609.0-2019 (Revision of IEEE Std 1609.0-2013)*, pp. 1–106, 2019.

[2] S.-J. Heo, Z. Chunwei, and E. Yu, "Response simulation, data cleansing and restoration of dynamic and static measurements based on deep learning algorithms," *International Journal of Concrete Structures and Materials*, vol. 12, no. 82, 2018.

[3] S. Chopra, G. Dhiman, A. Sharma, M. Shabaz, P. Shukla, and M. Arora, "Taxonomy of adaptive neuro-fuzzy inference system in modern engineering sciences," *Computational Intelligence and Neuroscience, Hindawi*, 2021.

[4] Y. Lei, "3 - individual intelligent method-based fault diagnosis," in *Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery*, Y. Lei, Ed. Butterworth-Heinemann, 2017, pp. 67–174. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780128115343000032

[5] C. Wu, S. Ohzahata, Y. Ji, and T. Kato, "Joint mac and network layer control for vanet broadcast communications considering end-to-end latency," in *Advanced Information Networking and Applications (AINA), 2014 IEEE 28th International Conference on*, May 2014, pp. 689–696.

[6] M. Sharifi-Rayeni, A. Hafid, and P. K. Sahu, "Dynamic spatial partition density-based emergency message dissemination in vanets," *Vehicular Communications*, vol. 2, no. 4, pp. 208–222, 2015. [Online]. Available: http://dx.doi.org/10.1016/j.vehcom.2015.07.002
[7] D.-j. Lee, Y. Deng, and Y.-J. Choi, "Back-off improvement by using q-learning in ieee 802.11p vehicular network," in *2020 International Conference on Information and Communication Technology Convergence (ICTC)*, 2020, pp. 1819–1821.
[8] H. A. Sayedahmed, E. M. Elgamal, and H. A. Hefny, "F-802.11p: A fuzzy enhancement for IEEE 802.11p in vehicle-to-everything communications," *International journal of Computer Networks & Communications*, vol. 14, no. 4, pp. 19–40, jul 2022. [Online]. Available: https://doi.org/10.5121
[9] F. Chbib, W. Fahs, J. Haydar, L. Khoukhi, and R. Khatoun, "IEEE 802.11p performance enhancement based on markov chain and neural networks for safety applications," *Ann. des Télécommunications*, vol. 76, no. 9-10, pp. 617–632, 2021.
[10] N. Septa and S. Wagh, "Optimization of contention window and relay selection for efficient routing using fuzzy logic model," *IEEE Access*, vol. 11, pp. 36 993–37 005, 2023.
[11] Z. Pei, W. Chen, L. Du, and H. Zheng, "Mac contention protocol based on reinforcement learning for iov communication environments," in *2021 IEEE 6th International Conference on Computer and Communication Systems (ICCCS)*, 2021, pp. 546–552.
[12] M. Slavik, I. Mahgoub, and F. N. Sibai, "The distance-to-mean broadcast method for vehicular wireless communication systems," in *2011 International Conference on Innovations in Information Technology*, 2011, pp. 371–374.
[13] E. Zhou, C. M. Vong, Y. Nojima, and S. Wang, "A fully interpretable first-order tsk fuzzy system and its training with negative entropic and rule-stability-based regularization," *IEEE Transactions on Fuzzy Systems*, vol. 31, no. 7, pp. 2305–2319, 2023.
[14] Y. Wang, J. Liu, J. Mišić, V. B. Mišić, S. Lv, and X. Chang, "Assessing optimizer impact on dnn model sensitivity to adversarial examples," *IEEE Access*, vol. 7, pp. 152 766–152 776, 2019.
[15] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard *et al.*, "Tensorflow: a system for large-scale machine learning." in *Osdi*, vol. 16, no. 2016. Savannah, GA, USA, 2016, pp. 265–283.
[16] P. A. Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. Wießner, "Microscopic traffic simulation using sumo," in *The 21st IEEE International Conference on Intelligent Transportation Systems*. IEEE, November 2018, pp. 2575–2582. [Online]. Available: https://elib.dlr.de/127994/