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Research Article

Load Aware Traffic Congestion Control Mechanism Using Fuzzy Logic

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Abstract

Recently, vehicular networks (VANETs) have emerged as promising technology for enabling communication between vehicles and infrastructures to improve road safety and driving experience. However, the dynamic nature of VANETs, characterized by rapidly changing traffic conditions and varying network load, poses significant challenges for reliable communication. Congestion control is a critical aspect of VANETs to prevent network saturation, reduce packet loss, and enhance overall system performance. In this context, the application of fuzzy-logic-based approaches offers a flexible and adaptive solution to dynamically adjust the network performance. This research introduced a fuzzy-logic-based congestion control mechanism for VANEts. The approach focused on dynamically adjusting the beacon busy ratio, road segment, and vehicle speed to address the fluctuating traffic condition, thereby mitigating congestion and enhancing vehicular network efficiency. Leveraging fuzzy logic, the proposed system can make route suggestions through the communication between roadside units based on input variables such as beacon busy ratio, road segment, and vehicle speed. On the result and analysis, the performance analysis of the system-based implemented Network Simulator-3 (NS3) and Simulation for Urban Mobility (SUMO) network simulation tool is used. Through simulation, the efficacy of the approach is demonstrated, showing its ability to adapt to evolving traffic dynamics and alleviate congestion on VANETs for enhancing network performance and reliability. The simulation result shows that our proposed system achieves a packet delivery ratio of 95%, throughput of 110 Kbps, and end-to-end delay of 1.93 seconds. This result shows that our scheme is feasible and effective.

Keywords

Load, Fuzzy-logics, Roadside Unit, Vehicle, Road Segment

1. Introduction

Vehicular ad hoc networks (VANETs) are a subset of mobile ad hoc networks (MANETs) that are used to communicate between vehicles to vehicles and vehicles to infrastructure. Vehicles act as nodes in a VANET, sending and receiving data without the need for a physical link [1]. VANET supports vehicles to communicate through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications) to control critical situations. VANETs use the IEEE 802.11p

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standard and Dedicated Short Range Communication (DSRC) for communication. For specialized short-range communication, the US Federal Communication Commission (FFC) has set aside 75 MHz of bandwidth at 5.9 GHz (DSRC) [2-4].

In urban areas, a significant increment of vehicles often leads to challenges like traffic congestion. The congested network results in a lack of eco-friendly, safe and reliable transportation. The effective congestion management method reduces the possibility of accidents. Congestion is currently widely regarded as one of the world's most serious issues. Because of the growing number of modes of transportation and the current low-quality road infrastructure, traffic problems are predicted to become substantially more widespread. Congestion is caused by a variety of circumstances, including rush hour, road construction, accidents, and even adverse weather. All of these causes, as well as a slew of others, can contribute to traffic congestion. Drivers who are unaware of the problem eventually join it, exacerbating the problem. The more severe the congestion, the longer it will take to clear once the source of the blockage is removed. Knowing the traffic conditions on the road ahead of time will allow a driver to seek alternate routes, saving time and money. When a large number of drivers have this capability, traffic congestion will be less severe, with only the vehicles in the congestion region affected.

In computing, fuzzy – logic is a form of many-valued logic that deals with approximate reasoning. Unlike binary logic, fuzzy logic allows various degrees of truth. This makes the fuzzy-based system to deal with uncertainty. In fuzzy systems, a set of linguistic rules is used to express the input-output relationship. Designing fuzzy rules for congestion control using fuzzy logic involves establishing the relationship between the inputs (load metrics) and outputs (control actions). Fuzzy logic is a popular approach for congestion control in VANETs due to its ability to handle the uncertainty and imprecision inherent in VANET environments. Fuzzy logic-based solutions can make intelligent decisions about channel access, transmission rates, and other congestion control parameters without requiring precise mathematical models [5-8]. Thus, this research focuses on proposing a load-aware congestion control mechanism for VANETs using fuzzy logic. The mechanism aims to dynamically adapt the network's congestion control parameters based on the current traffic load and network conditions, thus improving the overall network performance.

Contribution of the Research

1) Design an algorithm based on the load on the network using fuzzy logic and determine non-congested road segments.
2) Improve the traffic congestion through route suggestions between neighbors RSU.
3) The proposed scheme requires the neighbor RSU to reply with a congestion route index to gain the road segment status.

2. Related Works

The increasing quantity of cars on the streets is leading to issues with traffic. To enable seamless traffic movement, vehicles were under constant surveillance [1]. Smart traffic solutions will be implemented to identify vehicular accidents and mitigate traffic congestion. Numerous technologies are employed to avert traffic accidents. The authors [8] proposed a fuzzy approach to congestion control on VANET. Their approach in general used fuzzy sets based on metaheuristics optimization-based routing (MOR) communication for VANET. As fuzzy input travelling speed, link quality, trust factor, and inter-vehicle distance get fuzzy output. To test the validity of their work, they use the MATLAB tool. Based on simulation they improved the performance of the Internet of vehicles. However, the system selects a cluster head vehicle as a forwarder node, which creates a communication overhead on the vehicle itself.

The authors [9] introduce a V2V routing protocol by incorporating fuzzy logic and reinforcement learning mainly the use Q-Learning method. The fuzzy logic is applied to choose cluster heads and Q-Learning is used to select the effective route. The fuzzy input is derived from node centrality, node mobility and bandwidth efficiency as variable. The authors used the NS2 network simulation tool to test their algorithm in terms of end-to-end delay, routing overhead, and packet delivery. However, the algorithm does not consider further traffic conditions as its computation method is based on the current travel time at road segments and the number of queue lengths on the road [1].

The authors in [5] proposed secured routing using fuzzy logic in VANET against sinkhole attacks and Sybil attacks. Their goal is to forward large data by using TDMA and multi-trading. The use of TDMA channel is used to divide original data into frames. For route selection, fuzzy logic is used. To secure the routing cypher text encryption is used. For simulation, OMNet++ and SUMO tools were used based on end-to-end delay, throughput, and traffic collision performance metrics. However, forwarding large volumes of data and authentication schemes increases the computational overhead on the network.

The authors [10] proposed a fuzzy logic-based congestion estimation monitoring system for VANET. The author used image processing based on the KNN classifier to identify the congestion of the vehicular network. Using fuzzy logic and KNN classifier the vehicle is grouped according to light, moderate, and heavy congestion to make congestion. Their algorithm was tested using MATLAB tool to check the validity of the work. They show clearly the integration of image processing with fuzzy logic on VANET. However, other network performance indicators remain unconsidered in the paper.

The authors [11] proposed a fuzzy logic-based routing protocol for vehicular networks. This study focused on route selection, the source node gathers information as fuzzy input sets from lifespan, range, and orientation and selects the finest vehicle along the routing path. The authors [12] proposed Greedy Traffic Routing Protocol (GTARP) for VANETs is designed to enhance routing efficiency by considering traffic conditions and the dynamic nature of the vehicular environment. The protocol uses a greedy approach, where each vehicle forwards packets to the neighbor that is closest to the destination. However, the dynamic nature of vehicles makes it difficult to maintain stable routes. There is also a data overhead that increases results to manage routing effectively.

A vehicle ID-based congestion aware message (CAM) for beacon signals in the vehicle environment is presented by the Traffic Density-Based Congestion Control (TDCCA) Method for VANETs [13]. However, because the algorithm's computation approach relies on the current travel time at road segments and the number of queue lengths on the road, it ignores other traffic situations. In Vehicle to Infrastructure (V2I) communication, the affected vehicle in the collision notifies the other forwarder vehicle and RSU of the lane's present condition by sending a warning message. In order to avoid traffic jams and collisions, the following vehicle on the road decides to take an alternative route.

The authors [14] present a route suggestion protocol to suggest an optimal congestion-aware route in the network, taking into account both equipped and non-equipped vehicles. Simulation results showed greater performance and reduced travel time when working with the Internet of Vehicles (IoV) compared to traditional route suggestions protocols. With time, a surge in congestion occurs and the application of optimum throughput proves to be a more efficacious strategy in comparison to an abrupt reduction. The observed throughput exhibits constancy during non-congested periods but manifests variability in response to traffic volume on congested roads.

In general, the reviewed works demonstrate the effectiveness of fuzzy logic-based approaches for congestion control in VANETs. By leveraging the ability of fuzzy logic to handle uncertainty and make intelligent decisions, these solutions can adaptively manage network congestion and improve the overall performance of VANET applications.

3. Research Methodology

3.1. Load Aware Congestion Control Mechanism Using Fuzzy Logic

In this study, we propose load aware congestion control mechanism using a fuzzy logic algorithm to improve traffic congestion on the VANET. We define the VANET network as a set of N= {V, R, I), where V is the set of vehicles, R is the set of road segments, and I is a set of road intersections. We suppose that each road intersection area deploys the Road Side Unit (RSU). Each road segment has its length L. Thus, to get the traffic congestion condition all the components i.e., vehicles and RSU need to share all the current road conditions. This situation can improve highly degrade the network performance by balancing the load among the vehicles. For this purpose, each vehicle forwards road segment information and the RSU calculates some values for itself that are referred to as congestion route index. In the proposed work, we divide the overall process into three main stages as shown in Figure 1 [1].

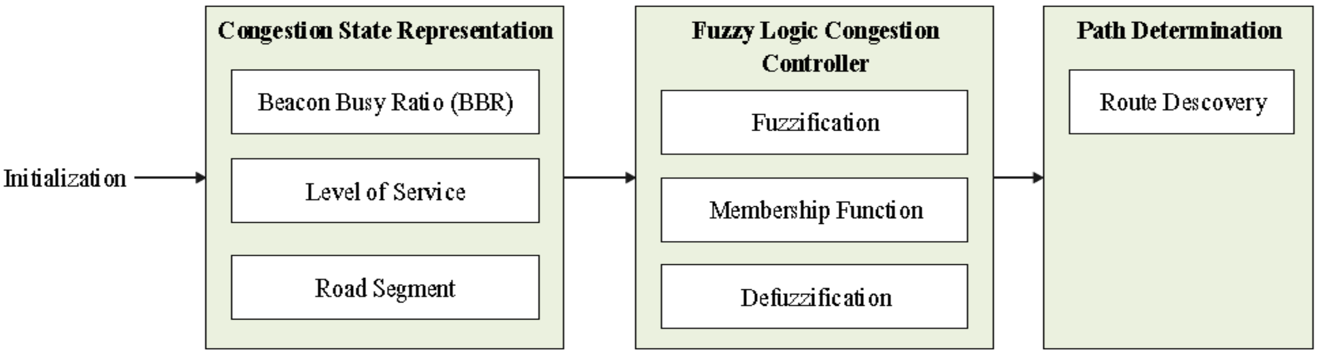

Figure 1. *Load Aware Priority Adaptive Congestion Control using Fuzzy-Logic.*

The first stage is initialization for the network model representation of the VANET network. We start by choosing the vehicle to Infrastructure (V2I) communication. The second stage is for congestion state representation, on the VANET, not all of the network is congested. Thus, to identify whether the network is congested or not we use the beacon busy ratio the information exchange between the vehicle and the V2I. Some information is level of service based on the speed of the vehicle, the road segment or the capacity of the road. The final stage is path determination, based on the fuzzy output of the information with neighbor RSU, it is used to suggest the road segment that has a better index in the network.

3.1.1. Stage 1: Initialization

(i). Nearest Neighbors

In VANET communication, the vehicle's direction, speed and location are unpredictable. On the road segment, the presence of a high number of neighboring vehicles results in higher congestion on the road. In our work, each RSU in the network keeps a list of all possible neighbor vehicles within the transmission range. To compute the distance between vehicles we use a Euclidean distance to identify the neighboring vehicles. Let us suppose that there are two vehicles V_1 and V_2 in the transmission range r of the RSU as illustrated in Figure 2. These vehicles are travelling with the speed of V_1 and $V_{2\ at}$ a time *t*. Thus, to calculate the distance D between vehicles D (V_1, V_2) at locations X and Y we use Eq. (1).

$$D(V1, V2) = \sqrt{(Xv2(t) - Xv1(t))^2 + (Yv2(t) - Yv1(t))^2} \tag{1}$$

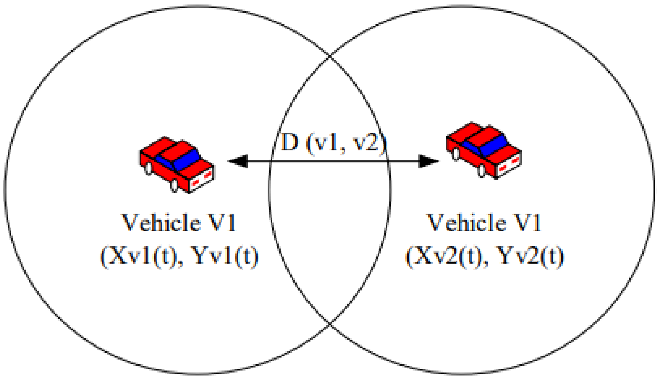

Figure 2. *Distance estimation between vehicles.*

(ii). Communication Model

On VANET neighboring vehicles, some vehicles are relatively placed closer than other neighbors. Such nodes can be considered as nearest neighbors (NN). Therefore, to get the physical distance we consider the received signal strength indicator (RSSI) mechanism. This RSSI mechanism uses the Pathloss model Frii's free space propagation model. Because, in the VANET environment, there are several causes to occur pathloss such as reflection, absorption, and deflection on the transmission medium. It has a significant advantage in measuring the transmission from transmitter to receiver. An RSSI-based [15] is computed to determine the neighbor nodes. The RSSI-based distance computed using Eq. (2).

$$Pi, j(d) = \frac{\rho iGiGj\lambda}{(4\pi)^2 d^2} \tag{2}$$

While ρi represents the transmission power, Gi and Gj represent the antenna gains of nodes i and j, respectively. Nodes j and i stand for the transmitter and receiver, respectively. λ Indicates the wavelength (meter) of the transmission signal.

Each node keeps a separate set of nearest neighbors (NNs) with their estimated location and speed information. If a node has a frequent number of NNs, then it means that the node has less opportunity to become a forwarder of other nodes. Nodes with a fewer number of NNs are vital and can perform more than others can.

Every node maintains an individual collection of nearby nodes that have been marked as nearest neighbors along with their approximate positions. If a node consistently has a significant number of connectivity neighbors, this implies that other nodes have fewer chances of selecting the mentioned node as a forwarder.

3.1.2. Stage 2: Congestion State Representation

(i). Beacon Busy Ratio (BBR)

Since the nature of the vehicular network channel is dynamically affected by the temporal arrival time of the vehicles on the road segment. To identify the congestion state, we used a Load Beacon Busy Ratio (BBR) scheme for the detection of congestion levels on the network extracted from vehicles. In VANET, vehicles communicate with in the area they use beaconing. The authors [16] described beaconing as "the process of periodically and locally broadcasting status information is a key communication pattern in vehicular ad hoc networks. The authors [17] noted, "Beaconing is one of the most important communication modes, which is used to advertise the presence of a car to its neighbor cars. The authors [16] investigated the impact of sending messages to vehicles to keep them aware and found that sending directly with single-hop to each other works better and faster than sending through multiple vehicles i.e. multi-hop. The BBR is defined by the following Eq. (3):

$$BBR = \frac{\sum_{i=1}^{n} M(v)}{Channel_{Capacity}} \left({}^{bytes}/_{sec}\right) \tag{3}$$

Where *M (V)* is the message received from neighbor vehicles that arrived at the RSU and *Channel Capacity* is the total link capacity for the queue in the congested network. The RSU computes the BBR of the congested queue value derived from available vehicles that are in communication with the RSU. Once the value of the current state of the road segment is extracted from BBR we then can define the minimum and maximum congestion threshold. This helps as later as an input for the fuzzification step.

Since our work focuses on vehicular communication, for maximum channel capacity we use a data rate range between 3 to 12 Mbps. The VANET commonly confront congestion due to road traffic over-burdening links beyond their capacity. On VANET, the acceptable maximum data rate as stated in [6] for a vehicle can move with a speed of up to 80km/h. By using these values, the BBR value lies between 0.2 and 0.6. The BBR value as it becomes between 0.2-0.43 means the road segment has a "Good" congestion state, if it is between 0.43-0.6 the road segment is an “acceptable” congestion state and if it is greater than 0.6 the road segment has “Poor” congestion state.

(ii). Vehicle Speed

The VS_{ratio} is used to identify the ratio of the total delay on a vehicle on a congested road and the total time of the vehicle, that derived from Eq. (4).

$$VS_{ratio} = \frac{\sum_i D_{T(i)}}{\sum_i T_{S(i)}} \tag{4}$$

Where D_T is the total travel distance of vehicle i on the road segment and T_S is the total time spent by vehicle i on the road segment. Based on the result obtained from VS_{ratio} we can identify the level of the serve of the road segment at the current time.

(iii). Road Segment Capacity

The RS_{ratio} is used to calculate the traffic link or capacity during maximum flow conditions at peak hours of the road by using Eq. (5).

$$VS_{ratio} = \frac{Vehicle\text{−}peack_{volume}}{Road\_capacity} \tag{5}$$

For RSU to suggest the most non-congested path towards the destination based on the CRI value through the control packet by broadcasting the CRI value to RSU. This process is done when the suggestion level path is the capacity of the road, then the RSU calculates the CR value later it used to share or exchange between neighbor RSU.

3.1.3. Stage 3: Fuzzy Logic-based Congestion Controller

In the fuzzy logic-based algorithm, during the RSU receives a message from vehicles, it proceeds to analyze the state of network congestion using fuzzy input load metrics. In our context, a fixed threshold value is used, to detect that the network is experiencing congestion beyond the defined threshold. We utilize the fuzzy inference mechanism to evaluate the real-time performance of road status whether it is congested or not. This fuzzy inference system consists of three steps: Fuzzification, Fuzzy inference and Defuzzification. In the First step, each RSU converts its input value into a membership degree of fuzzy set in this work; we use a triangular membership function to convert the input into fuzzy value. In the second step, each RSU performs fuzzy inference based on a set of If-Then rules using the membership degree obtained in the fuzzification step. The last step is defuzzification, in which the result of fuzzy inference is converted into the crisp value we employ a Congestion Threshold (CT) method for all fuzzy logic controllers in this work. This module called on every encounter between each pair of vehicles and RSU to learn the best route for the vehicle.

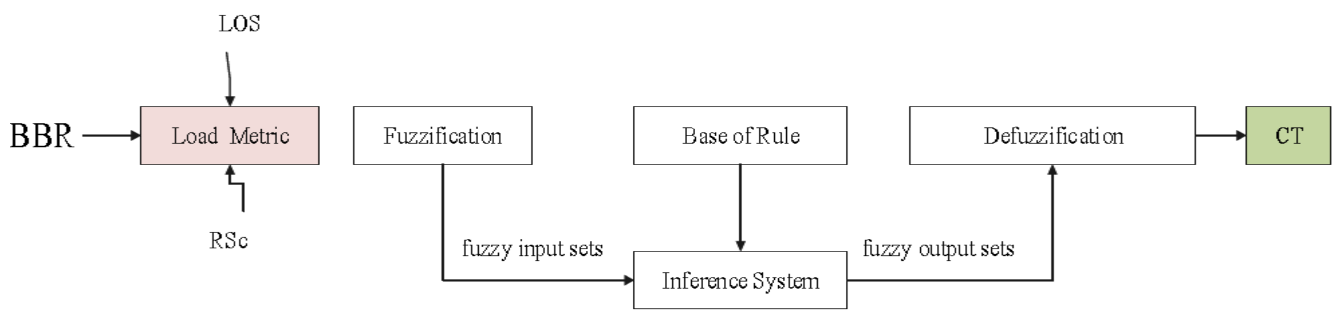

Figure 3*. Fuzzy logic-based controller.*

(i). Fuzzification

In this fuzzification process, choosing fuzzy rules for congestion control involves establishing a good relationship between the inputs (load metrics) and outputs (control actions). As input relevant load metrics that will serve as inputs to the fuzzy logic controller are Beacon Busy Ratio (BBR), Level of Service (LOS), and Road Segment Capacity (RS_c). The selection of fuzzy sets is highly dependent on the specific context and requirements of the congestion control problem in vehicular ad hoc networks. It is essential to strike a balance between simplicity and expressiveness to ensure that the fuzzy logic controller can effectively capture the nuances of congestion control. Based on the load metrics, traffic density is described by terms such as "Good," "Acceptable," and "Poor."

(ii). Base Rule

After fuzzification, we need to determine the method for combining the fuzzy rules to make a control decision. These methods use fuzzy reasoning to aggregate the rule outputs and produce a crisp control action. Thus, we implement the fuzzy rules in a rule base within the fuzzy logic controller. The rule base consists of the defined linguistic terms, antecedents, consequents, and weights. During runtime, the input values are evaluated against the fuzzy rules to determine the appropriate control action. For each fuzzy input set, we mapped a total of 9 rules in the IF-THEN conditional statement. Table 1. emphasis the complete set of base rules that used the three input fuzzy variables and one out numerical variable. That numerical variable represents the congestion Threshold (CT) of the road at time t.

Table 1. *Fuzzy rules.*

Rule No	BBR	Los	RS_c	CT
1	"Good"	"Good"	"Good"	CT ≥ 0.1 AND CT≤ 0.63
2	"Good"	"Acceptable"	"Good"	CT > 0.63 AND CT≤ 2.4
3	"Good"	"Poor"	"Acceptable"	CT ≥ 1.2 AND CT ≤ 2.06
4	"Acceptable"	"Good"	"Acceptable"	CT ≥ 0.3 AND CT ≤ 0.83
5	"Acceptable"	"Acceptable"	"Acceptable"	CT ≥ 0.63 AND CT < 1.5
6	"Acceptable"	"Poor"	"Poor"	CT > 1.4 AND CT ≤ 2.26
7	"Poor"	"Good"	"Good"	CT ≥ 0.3 AND CT ≤ 0.86
8	"Poor"	"Acceptable"	"Acceptable"	CT ≥ 0.73 AND CT ≤ 1.63
9	"Poor"	"Poor"	"Poor"	CT ≥ 1.5 AND CT ≤ 2.4

(iii). Defuzzification

The defuzzification process converts the aggregated fuzzy outputs into crisp control actions. This process involves summarizing the fuzzy outputs and selecting a representative value that corresponds to the desired control action. During defuzzification, it is better to specify the control actions that the fuzzy logic controller will take based on the inputs. On these actions by using crisp output congestion notification triggered. As crisp output, we use the congestion threshold (CT).

(iv). Congestion Threshold (CT)

The CT value was derived from the BBR, L_{os} and RS_c mapped input variable by using the maximum value of the state. For example, in Rule 1 there are "Good", "Good", and "Good" which represent the values 0.3, 0.1, and 0.5 respectively, then the CT value lies between 0.1 and 0.63 thus the result indicates the road shows good congestion threshold value. Similarly, if we then take Rule 5 by summing up the numerical value again, we dividend by 3 we get the CT value between 0.63 and 1.5 which indicates the road congestion has an acceptable congestion rate. Finally, by Rule 9 the result of the CT value lies between 1.5 and 2.4, which has a poor congestion state. For CT value, as demonstrated in Eq. (6).

$$\text{threshold}(C_T) = \begin{cases} C_T \geq 0.1 \text{ and CT} \leq 0.63, \text{No Congestion on the road.} \\ C_T > 0.63 \text{ and CT} < 1.5, \text{acceptable congestion on the road.} \\ C_T > 1.5 \text{ and CT} \leq 2.4, \text{congestion on the road.} \end{cases} \tag{6}$$

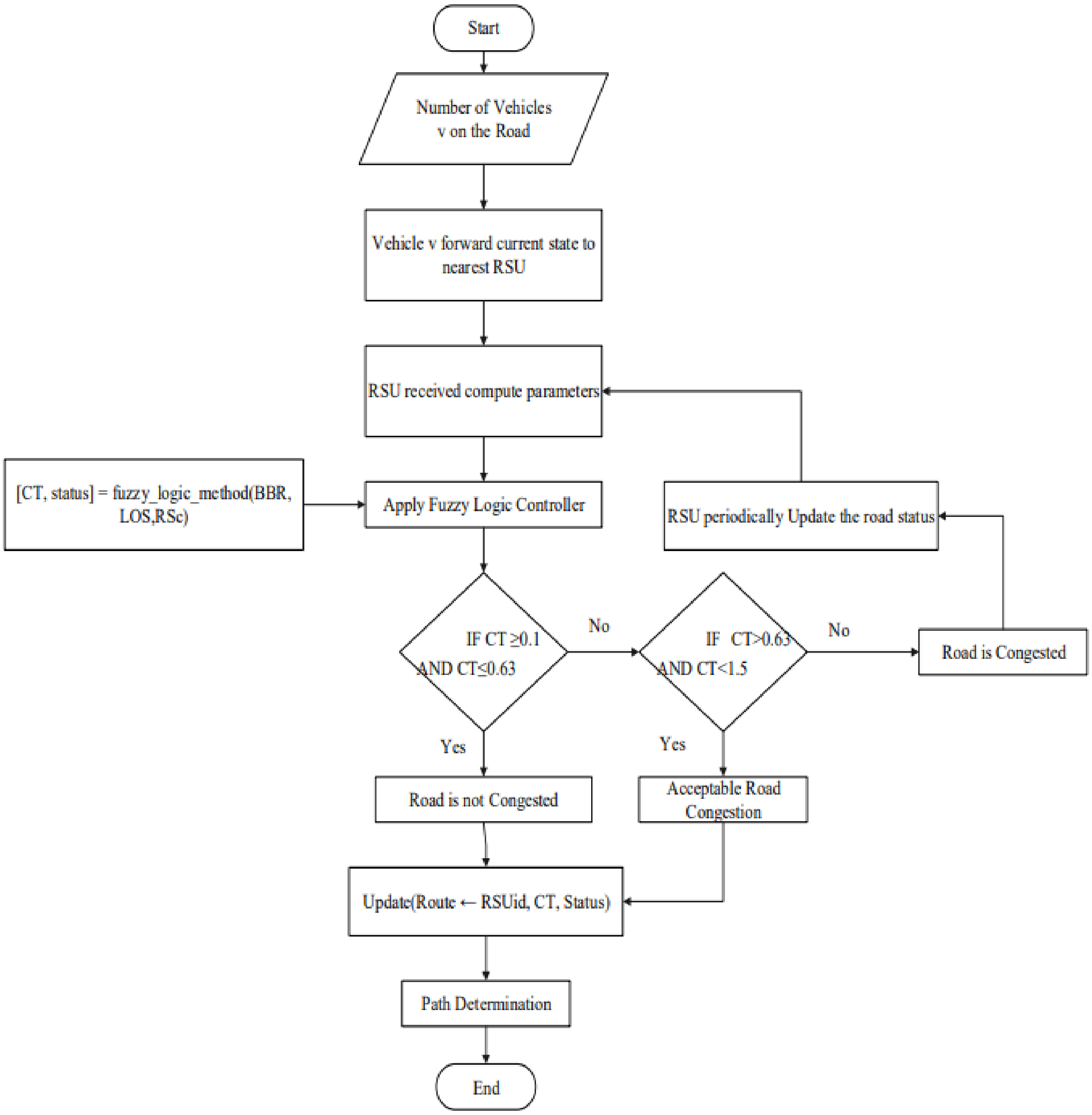

Figure 4. *Proposed congestion control using fuzzy logic Flowchart.*

Algorithm 1: Proposed Method Algorithm

Input: Beacon Busy Ratio (BBR), Level of Service (L_{os}), Road Segment (RS_c)

Output: Congestion Threshold

procedure void proposed Method (BBR, L_{os}, RS_c)

Vehicle forward current status of the road

RSU receive computing parameters from vehicle

while (Vehicle in RS_{id})

RSU calculates BBR, L_{os}, RS_c based on Eq. (3), (4), (5)

[CT, Status] =fuzzy_logic_method (BBR, LOS, RSc) //Apply Fuzzy Logic Controller

if CT≥0.1 and CT≤0.63 then //Maximum threshold based on Eq. (7)

Road is not Congested

RSU periodically update road status

else if CT>0.63 and CT<1 then

Road has Acceptable Congestion Status

RSU periodically update road status

else

Road is Congested

Update (Route ← RSUid, status, CT)

end if

end while

end procedure

3.1.4. Stage 4: Path Determination

Once on the congestion level, the CRI is initiated using the vehicle traffic data, route suggestion step begins to calculate an optimal route. Ideal route suggestion is refreshed at each intersection, taking into account the data provided by the RSU. We also consider how busy the roads are and try to choose routes with less traffic to avoid being stuck. RSU receives new information from a central location and can share their own information with other RSU nearby. The congestion in the VANET was identified by utilizing the communication channel condition. The traffic load in the channel is estimated, and if the level is reached based on the threshold, the traffic congestion is identified; consequently, the congestion condition is forwarded to the nearby vehicles to alert them about the traffic congestion. If a traffic congestion threshold state is detected using the fuzzy set, then the RSU forward the path determination packets to the vehicles.

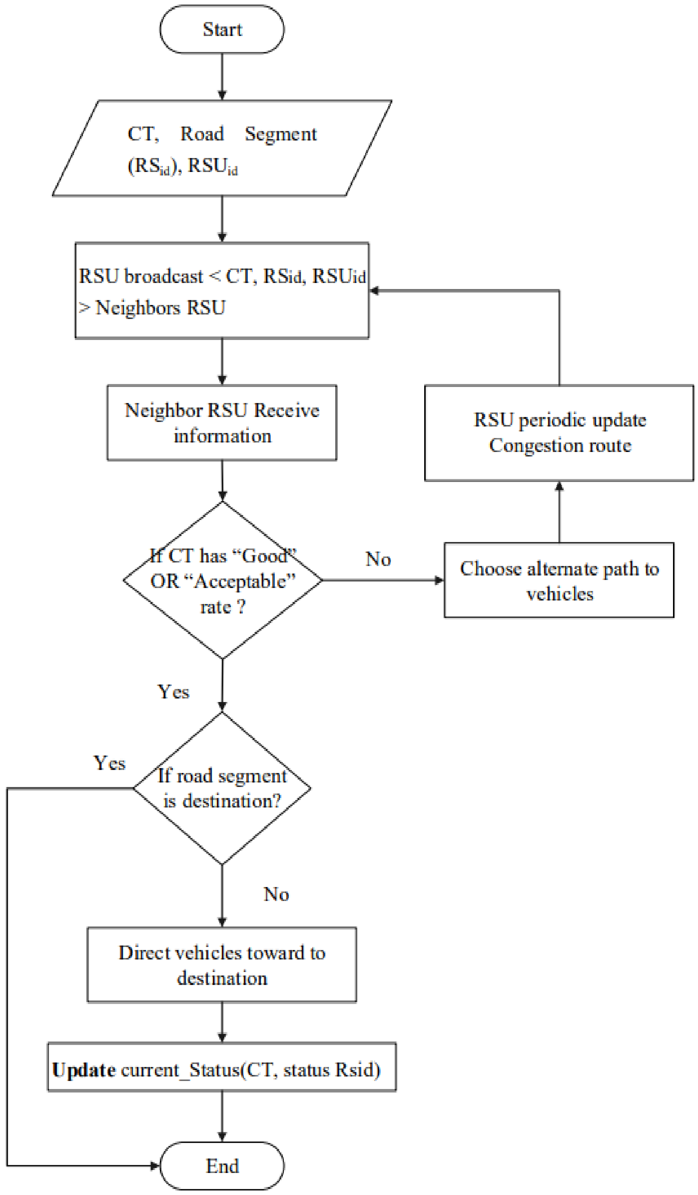

Figure 5. *Path determination flowchart.*

Each vehicle on the road periodically sends a message to their nearby RSU and updates the road segment information at time t. Each RSU keeps its associated road segment information in the route suggestion table. The RSU exchanges the CT information with other RSUs and sends the road segment information to the data center as well. Congestion Suggestion Table (CST) includes the optimal route from an origin to destination considering the travel time and route congestion. The congestion information exchanging between RSU has the following steps.

RSU gather road information from the vehicles on the road segment. Based on our assumption each road intersection is deployed with a special RSU to gather information and based on the information RSU calculates the CT value.

RSU send a request to neighbor RSU. The RSU forward its CT value with additional information. The RSU ID, Road Segment ID (RS_{id}), and CT.

$\langle RSU_{id}, RS_{id}, CT\rangle$

RSU receive information from neighbors RSU and suggests route path discovery. After the RSU received a reply from neighbor RSU about road segment information, it suggested the vehicle that has a less congested road segment towards to vehicle destination.

Then the RSU updates current congestion status of the road segment.

Algorithm 2: Path Determination Method Algorithm

Input: CT, Road Segment (RS_{id}), RSU_{id}

Output: Route Path

RSU broadcast <RSU_{id}, RS_{id}, CT>

for each neighbor RSU_{id} compare CRI value do

if the CT has a "Good" OR "Acceptable" state then

if the road segment is destination, then

break; //vehicle reach destination

else

Road Segment with good CT value is suggested for the route

UPDATE current_status (CT, RSid)

end if

else

Road Segment with good CT value is Not suggested for the route

UPDATE RSU information

end if

end for

end procedure

3.2. Experimental Setup

For conducting the simulation, choose the popular simulator Network Simulator-3 (NS-3) is used, as the simulator of the proposed protocols and a Simulation of Urban MObility (SUMO) simulator [18].

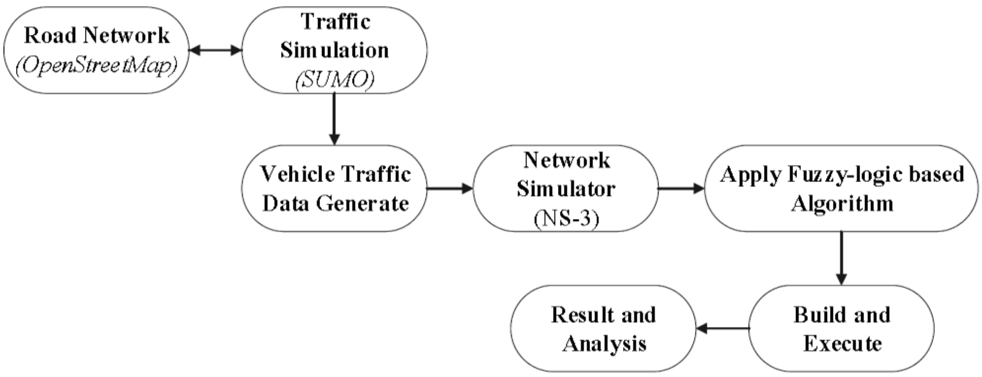

***Figure 6.** General procedures applied during simulation using SUMO and NS3.*

The proposed protocol performance is compared with the existing routing algorithms based on the simulation parameters listed in Table 2.

***Table 2.** Experimental Parameters.*

Parameters	Value	Unit
Operating System	Ubuntu 16.04 LTS	-
Simulation Tool	NS3, SUMO	-
Area	1 x 1	Km^2
Speed of Vehicle	50-150	Km/h
Number of Lane	2	-
Number of Vehicles	100	-
Bandwidth	75	MHz
Message Size	Beaconing 3-12	Mega byte
Mac Type	802.11p	-
Transmission Rate	5.850 – 5.925	GHz
Routing Protocol	AODV	-

4. Result Analysis and Discussion

In this section, we discussed the result of the load-aware congestion control for VANETs using fuzzy logic analyzed and discussed in terms of packet delivery ratio, throughput and end-to-end delay. To compare the proposed method's effectiveness based on performance evaluation metrics, we use T2FSC-MOR [8] and GTARP [12] protocols. The first T2FSC-MOR is fuzzy based approach on congestion control on VANET. Their approach in general used fuzzy sets based on metaheuristics optimization-based routing (MOR) communication for VANET. Moreover, GTARP is a non-fuzzy-based approach designed for VANETs to enhance routing efficiency by considering traffic conditions and the dynamic nature of the vehicular environment. The reason for selecting these two different protocols is it makes as compare our work in broad.

4.1. Packet Delivery Ratio

In our experimental result, the packet delivery ratio performance of the system as shown on as shown in Figure 7. The plot shows the proposed method demonstrated a significant improvement in PDR compared to T2FSC-MOR mechanisms in VANETs. The numerical value for the proposed scheme has a 95% PDR value when the density is a lower congested area. Whereas the T2FSC-MOR shows 92% PDR and GTARP shows 85% value. Therefore, our proposed method has achieved better performance in terms of PDR under the congested network. The dynamics adjustment of transmission rates in our approach effectively optimized network resources leading to a higher proportion of successfully delivered packets.

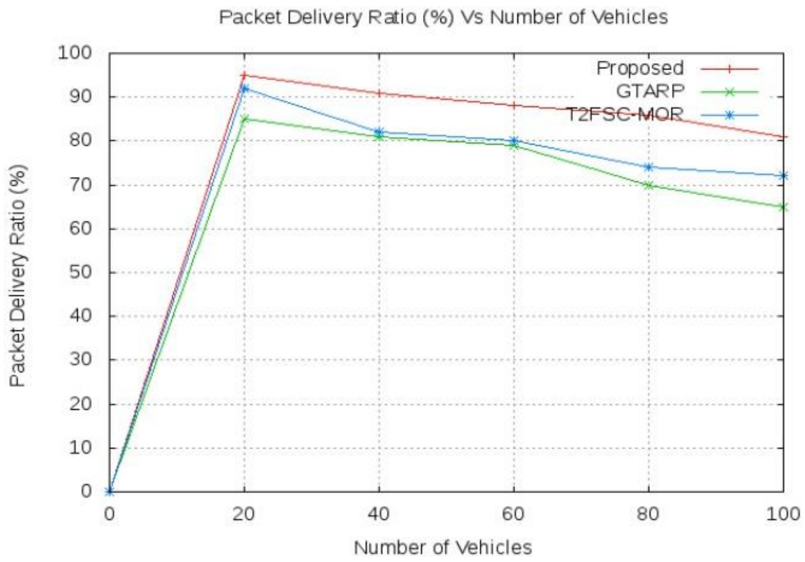

Figure 7. *Packet Delivery Ratio Vs Number of Nodes.*

4.2. Throughput

From the simulation result, the average throughput result of our scheme result 110 Kbps. Whereas in T2FSC-MOR, 98 Kbps throughput and GTARP, 64 Kbps was reached as depicted in Figure 8. The simulation result shows that the more the number of nodes increases, the more the data delivery rate also increases on each scheme. Here, each scheme shows less significant difference, under a low density of nodes. However, when the number of vehicles increases, the proposed scheme has good performance. The throughput analysis revealed that the proposed method results in more efficient utilization of network resources and improved data delivery rates.

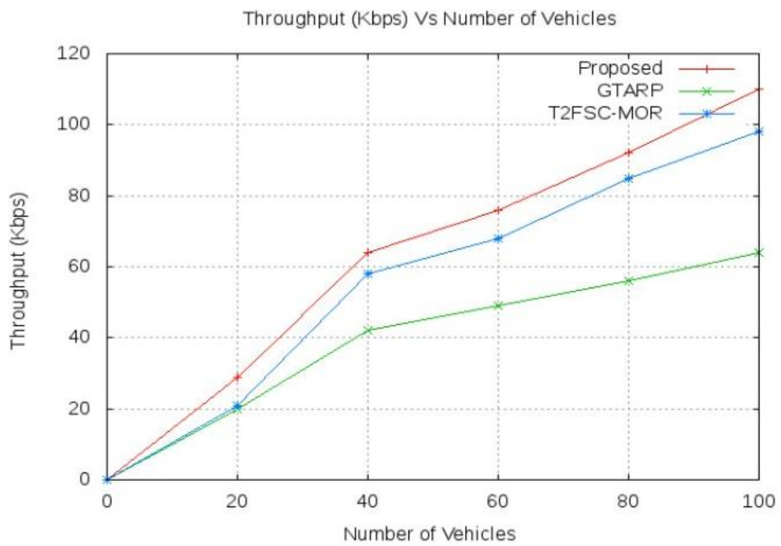

Figure 8. *Throughput vs. number of Nodes.*

4.3. Average Latency

In the simulation scenario, we compare and analyze the end-to-end delay of each fuzzy-based algorithm in different node-density environments. Figure 9, represents the latency of each scheme; the simulation result shows each scheme shows a less significant difference. Meanwhile, if we get the end-to-end delay in terms of 100 vehicles, the proposed method outperforms better average latency of 1930 ms than the T2FSC-MOR (2570 ms) and GTARP (2600 ms) protocol. The end-to-end analysis indicates that our method efficiently minimized packet travel time from the source to the destination.

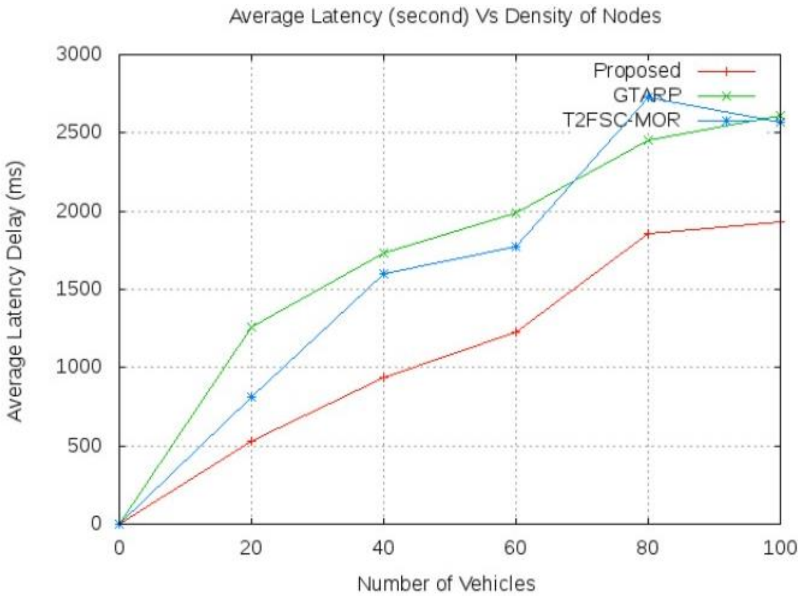

Figure 9. *Average Latency vs. number of Nodes.*

5. Conclusion

In conclusion, this work offers a traffic load aware congestion control mechanism based fuzzy logic approach on VANETs. It uses fuzzy logic to look at how to put information together to control traffic congestion. Based on fuzzy input, it suggested a method that uses a beacon busy ratio to improve the congestion on the road. The result of our method demonstrated the effectiveness of the proposed approach in improving PDR, throughput and end-to-end delay. By considering traffic load dynamically adjusting network parameters, the fuzzy logic-based scheme successfully addressed the congestion issue in VANETs. It showed that our algorithm has a good fit with the way data is collected and arranged. To validate the proposed algorithm, a set of experiments was conducted to determine the effectiveness of the proposed routing algorithm based on three simulation scenarios using the NS-3 simulator and SUMO network. The proposed workload-aware congestion control mechanism-based fuzzy logic approach on VANETs compared to T2FSC-MOR and GTARP algorithms based on packet delivery ratio, Throughput, and end-to-end. The simulation result shows that our proposed system improves the Packet Delivery Ratio to 95%, Throughput to 110 kbps, and end-to-end delay to 1930 ms. Therefore, based on the simulation result we observe that the proposed method shows better performance.

Abbreviations

VANET	Vehicular Ad Hoc Network.
IEEE	Institute of Electrical and Electronics Engineers
FFC	Federal Communication Commission
RSU	Road Side Unit
DSRC	Dedicated Short Range Communication
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
MANET	Mobile ad Hoc Networks
SUMO	Simulation for Urban Mobility
MATLAB	MATrix LABoratory
KNN	K-Nearest Neighbors
GHz	Gigahertz
OMNet++	Objective Modular Network Testbed
TDMA	Time Division Multiple Access
NS-2	Network Simulator-2
NS-3	Network Simulator-3
CAM	Congestion Aware Message
GTARP	Greedy Traffic Routing Protocol
MOR	Metaheuristics Optimization-based Routing

RSSI	Received Signal Strength Indicator
IoV	Internet of Vehicles
TDCCA	Traffic Density-Based Congestion Control
BBR	Beacon Busy Ratio
PDR	Packet Delivery Ratio
CST	Congestion Suggestion Table
CT	Congestion Threshold
CRI	Congestion Control Index
RS	Road Segment
VS	Vehicle Speed
T2FSC-MOR	Type-2 Fuzzy Sets Based Clustering with Metaheuristic Optimization Based Routing
LOS	Level of Service
NN	Nearest Neighbors
ID	Identification

Conflicts of Interest

The authors declare no conflicts of interest.

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