Eng. Sci., 2024, **28**, 1056

Engineered Science
DOI: https://dx.doi.org/10.30919/es1056

ECFL-IoVT: Emergency Communications using Fuzzy Logic for Internet of Vehicle Things

Chetana Hemant Nemade* and Uma Pujeri

Abstract

The Internet of Things (IoT) currently examines vehicle ad hoc networks (VANETs) for usage in intelligent transportation systems. For example, the widespread use of various automobile sensors has opened up new opportunities for enhancing routing performance in VANETs. This research proposes ECFL-IoVT, Emergency Communications using Fuzzy Logic for Internet of Vehicle Things. Finding the highest-quality reliable pathway among an origin and an end node is the foundation of the logic for the Internet of Vehicle Things protocol, which builds on hybrid fuzzy and ACO techniques. In ECFL-IoVT, the path finding process is intelligently enforced restrictions and the fuzzy control system are constrained extra overhead controls reducing the number of routing requests. The hybrid fuzzy logic rule selects the next reliable vehicle for data transmission through the rules evaluation towards the emergency vehicle to inform about the currently available freeway. The systematic and robust rules were introduced by considering various parameters such as mobility, congestion, and queue quality. By computing an improved fitness function, the type-2 fuzzy logic system for this contribution intelligently chooses the most stable and ideal path out of all known routes. Comparing ECFL-IoVT to other routing protocols, the simulation results show that it significantly upgrades the network performance, 'Routing Overhead', 'Packet Delivery Ratio', and 'Delay'.

Keywords: Internet of Vehicle things; Fuzzy logic; Emergency communication; Routing protocols; Fitness function.
Received: 16 May 2023; Revised: 25 September 2023; Accepted: 28 September 2023.
Article type: Research article.

1. Introduction

Mobile Adhoc Network (MANET) is a particular type of Adhoc Network that composes many wireless-mobile nodes which operates excluding the aid of a centralized control system and with little to no infrastructure. These networks have dynamic topologies, energy restrictions, and bandwidth restrictions. For example, IoT-connected VANET (Fig. 1), a specific class of IoT, offers a variety of distinctive properties, including predictable mobility, freedom from constraint energy, and quick adjustments to the network architecture.[1,2] Compared to MANETs.[3,4] in these networks automotive machines that are relatively long have avoided restrictions in exothermic reaction.

VANETs allow for communication involving automobiles close to one another and between moving vehicles and permanent units installed in specific places, including driveways and junctions. V2V (Vehicle-To-Vehicle) and V2I (Vehicle-To-Infrastructure) are two modes of communication that exist within networks (V2I). In vehicle-to-vehicle (V2V) communications, automobiles that are close to one another share data via Dedicated Short Range Communications (DSRC) and Wide Area Voice Exchange (WAVE), among other technologies.[5] In contrast, vehicle-to-infrastructure (V2I) communications are linked to roadside infrastructures to exchange data.[6] Inter-vehicle networks raise passenger pleasure and enjoyment, promote safe driving, and improve traffic flow.

Vehicle ad hoc networks do face several challenges, though. These challenges include deteriorating signals, a bandwidth cap, security and confidentiality issues, connection problems, and routing. Nevertheless, when signals of danger are sent promptly after collisions and accidents, it may be possible to stop further accidents from occurring. Reliable data packet routing can achieve this goal. Therefore, to improve vehicle security and please consumers, a routing system that could transfer data packets quickly and with the fewest packet losses

Dr. Vishwanath Karad, MIT World Peace University, School of Computer Engineering and Technology, Pune 411038, India.
**Email:* chnemade@mitaoe.ac.in (C. H. Nemade)

was developed.

From the source node making a path through middle nodes till the destination node is particularly challenging because of high movement of vehicles, restrictions on wireless sources, and frequent wireless channel losses. Each wireless link that makes up the route is essential to its effectiveness.[5,7,8] These networks present significant obstacles for routing. Vehicle traffic continuously modifies the topology of networks.[9] Additionally, significant increases in routing overheads result from large-scale network expansion.[2,10,11]

Preventing the routing of the VANET from becoming stuck in the optimum local presents another issue.[12] Peer-to-peer networks employ several strategies, to improve efficiency of routing, just as other networks and wireless communication systems.[13–15] To enhance routing in VANETs, a variety of techniques introduces. To determine the best path, various communication protocols use the structure of the intermediary links.[16] In contrast, others[17] base their designs on the location of the vehicles.

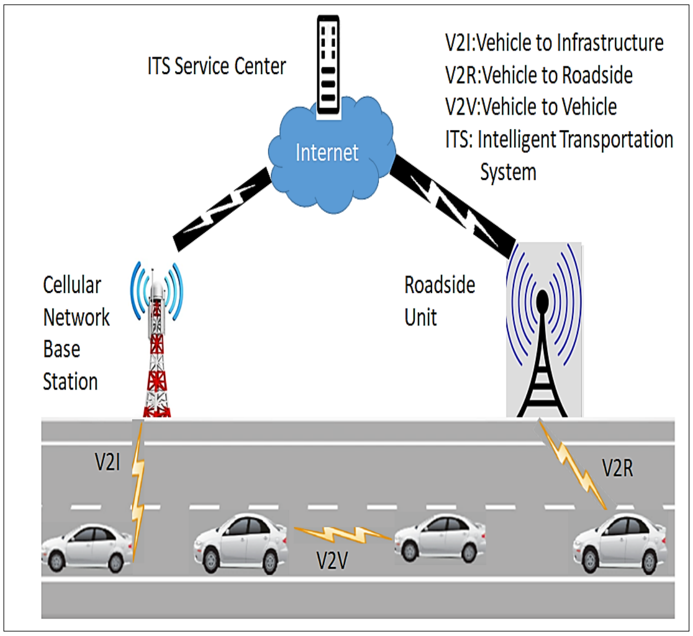

Fig. 1 IoT Connected VANET.

The latter focuses on where connections are located and anticipating where the vehicle will go next to identify the best path.[18–20] As for introducing routing protocols, fuzzy logic is also highly useful.[21,22] Several studies use bio approaches to determine the best routing. These techniques provide low-complexity solutions to compute problems while particularly effective for large-scale VANETs.[23–26] A hybrid approach may thus be quite successful.

This research suggests a revolutionary emergency communications system for the Internet of Things for vehicles that solve the issue from earlier investigations (ECFL-IoVT). To inform the emergency vehicle about the currently open motorways, we develop the hybrid fuzzy logic[27–29] rule that chooses the following trustworthy vehicle for data transfer. Systematic and reliable guidelines consider various factors, including mobility, congestion, and queue quality. For this contribution, we will employ the type-2 fuzzy logic system. This protocol cleverly used fuzzy techniques by providing new fitness functions that consider numerous crucial factors when determining the best regular route connecting the origin and the target nodes.

The Fuzzy Logic algorithm for Emergency Data Transmission initially determines the pathways in the sender. Then it calculates the fitness function based on parameters like velocity, traffic, and distance to determine which route is the best and free from the other available routes. The NS2 simulator determined that the essential network statistics, including Packet Delivery Ratio, Throughput, communication overhead, and delay, are 90.4871, 233.42, 2.75, and 0.17758, respectively.

The rest of this work follows: The past research in this area is reviewed in Section 2. A summary of a few important concerns related to fuzzification is given in section 3. In section 4, ant colony optimization is explained. Procedure and experimental strategy are presented in Section 5. The proposed routing protocol (ECFL-IoVT) and performance parameter and metrices in Section 6. Section 7 contains the simulation findings and a performance evaluation criteria report. The task from Section 8 has now been finished.

2. Literature survey

Routing is a challenging problem with VANETs, as was previously mentioned. This section reviews the most significant initiatives toward creating a routing algorithm for VANETs.

This protocol offers a favorable profile for data packet delivery rates and transfer delays. This protocol's data packet transmission rate will significantly increase with a more precise choice of carriers.[17] Selecting appropriate carriers, for instance, can be done by choosing municipal buses that stop at various places according to a schedule.

ECFL-IoVT uses fuzzy logic to choose the best reception connections for appropriate route requests (RREQ) in contrast to AFMADR. Designing efficient fitness functions depending on the lifespan of the linkages helps create stable pathways. In addition, selecting a reliable route increases packet delivery rates and decreases packet loss.

Using trust in MANET's forbidding search as its foundation,[22] has suggested a multi-level routing protocol. The top cluster head links display in a table. The most effective linkages are chosen based on distance, speed, and direction. Therefore, lower link failure rates and packet losses attribute to this protocol. However, to compare this protocol to other protocols, the overhead has yet to be considered.

For the ant colony optimization (ACO) protocol, "F-ANT"[2] has created an enhanced, fuzzy logic inference system. ACO, designed for VANETs, uses elements including bandwidth, signal strength at the receiver, and congestion criterion to assess the reliability of the link. This protocol needs to be improved by high overhead since it uses fuzzy logic and an ant colony algorithm.

When looking for routes to a destination[30], R2P employs a route discovery process. Then, although it might only sometimes choose the fastest path, it chooses the safest one. The delays decrease by this routing strategy, which is more effective than the alternatives. Its message transmission is minimal at a few preset simulating rates, but it does not outperform other approaches in terms of overhead.

Fuzzy logic is used in this protocol to evaluate the wireless link while considering many factors, including the amount of available bandwidth, the link's quality, and the vehicle's direction. Then, it discovers the optimum route through messages such as Hello and RREQ. This protocol's independence from lower layers explains its flexible and helpful routing capabilities. Its overhead performance, however, is not favorable.

By using fuzzy logic to restrict route discovery and reduce the available network control packets, the ECFL-IoVT in this article lowers overhead.

The method described in Ref. [31] recognises hazardous conditions brought on by quick shifts in topology and selects the best route to the target node using a location-based strategy that incorporates fuzzy logic and the BFOA (Bacterial Foraging Optimisation Algorithm).

The computations get incredibly difficult as the population grows, although this strategy results in fewer delays and faster delivery rates. However, this has a higher processing complexity than our metaheuristic technique.[31] When a node wants to transfer data packets, AODV[32], a dynamic protocol based on Bellman-Ford, establishes routes.[33] Discover, data transfer, and route maintenance are the three steps of AODV. Its usage of sequence numbers is what sets AODV apart from other protocols.

Data transfer is possible after the route is chosen. If any links are lost during the maintenance phase, this step will help find a replacement route. But due to its recurrent baking, this protocol consumes a lot of bandwidth.

By buffering the nodes, this technique for enhancing GPRS routing performance in Ref. [34] reduces network congestion. The transference nodes consequently select from the nodes with greater probability assignments.

The best local problem is not addressed by this protocol, which also provides a recovery method.[34] FCAR (Fuzzy Control-Based AODV Routing) protocol described in Ref. [35] uses fuzzy logic and fuzzy control to determine the best course of action. Two factors used to evaluate routes are their length and the percentage of vehicles traveling in a single direction. However, in contrast to AODV, it generates additional overheads when there are few network nodes.

By limiting the route discovery phase and utilizing fuzzy logic to choose the links receiving RREQ, ECFL-IoVT, in contrast, has been able to regulate the overhead in a generally adequate manner.[36]

The relay vehicles in the candidate set are only as good as the accuracy of this forecast.[37] Depending on how valuable a relay device is, it will have a different priority. This algorithm's development should have considered the effects of variables like packet length and transfer stages to avoid getting false results.

Broadcast storms, network splinters, sporadic vehicle connectivity, and capacity constraints are only a few of the significant problems that data transmission in VANETs faces. An information-dissemination protocol for VANETs that distributes emergency messages in various scenarios and traffic conditions. DDP4V uses segmentation of a vehicle's transmission region (NFV) to choose the best next-forwarding vehicle in heavy traffic situations.

To ensure message delivery during periods of low traffic, it separates a vehicle's transmission region into three independent segments. Then, it chooses one or more vehicles inside the highest priority segment to convey the message to all nearby vehicles. As a result, DDP4V has the ability[38] to offer effective data dissemination in various VANET settings with fluctuating traffic levels. Furthermore, it exhibits respectable performance in three different evaluation situations—a highway scenario, two urban scenarios, and a network split scenario.

Internet of Things in Vehicles (IoT-V)[39] is evolving as a global variety of vehicular networks. The underlying idea behind IoT-V is the newly developed notion of the associated Internet in intelligent transportation systems. IoT-V's primary goals are to commercialize vehicular networks and computerize extra vehicle security and competency elements. It proposes to use the analysis to confirm that implementing the mediator system as a stunning upgrade to the routing methods is practical. The main objective is to provide a multi-mediator routing method for VANETs. Four mediators are working in unison to find the best routes and reduce traffic within the network, forming the foundation of this novel routing strategy. An effective hybrid clustering method for traffic congestion in smart cities that uses IoT-enabled vehicular ad hoc networks to distribute data.

Route finding performance in VANETs demonstrates to be enhanced using discrete forms of the cuckoo search optimization (DCSO) algorithm[40,41] precisely the random walk approach. Furthermore, it demonstrates that the suggested solutions perform better in various vehicle density scenarios. To assess how well they perform in actual use, they can also expand to the situation of actual data transfer in more realistic VANET scenarios.

3. Proposed methods

3.1 Fuzzy logic

Things that are unclear or ambiguous are said to as fuzzy. From Fig. 2, The four fundamental stages of fuzzy logic control are Fuzzification, Knowledge Base, Inferences, and Defuzzification. Fuzzy values are created using linguistic variables and membership functions.

The second stage introduces a small collection of rules which are used to take a decision based on the final fuzzy value.The rules present in the rule base are used to generate fuzzy decisions during the third inference step.[42–48]

During the last stage, non-fuzzifying procedures are transformed into digital values and the membership output functions are predefined. When it's impossible to define non-linear models or simple mathematical procedures for complex processes, this approach can be pretty helpful. Without using mathematical models, fuzzy logic is utilized to solve difficulties related to routing because it can handle erroneous and variable input. Using linguistic, non-digital variables, fuzzy logic could interpret approximations of data to describe the facts.[8]

3.2 Ant colony optimization

Marco Dorigo (1990) created the Ant Colony Optimization technique, which was purely based on how ant colonies foraged for food. Ants are eusocial insects that place a higher priority on the long-term health and survival of their communities than on the survival of particular kinds. Pheromone connection and sounds are the main means of communication between them. The ants produce pheromones, organic chemicals that influence how other members of their species behave in social situations.

These chemicals are hormone-like substances that function outside of the body of the individual secreting them, having an impact on how other people behave. Since most ants reside on the ground, they usually use the soil's surface where they can create pheromone trails for other ants to follow (smell).

The basic idea behind ACO.[43] is to observe the ants as they quickly depart their social nests in search of food. Ants live in communal nests. In the beginning, ants initially start to scurry aimlessly in and out of their nests in quest of food. This random search produces many pathways from the nest to the food supply. A piece of the meal is now carried back by ants with the right concentration of pheromones on its return trip, depending on the food's quality and quantity.

According to the outcomes of these pheromone trials, the likelihood that the following ants will select a specific path would act as a compass for their trek to the food source. The basis for this possibility is unquestionably the concentration and velocity of pheromone evaporation. Because the pheromone evaporation rate also influences the length of each path, the length of each path may be simply explained.

For simplicity's sake, just one of the routes within the food supply and the nest of ants are shown in the diagram below. The following section looks at each phase (Fig. 2):

Stage 1: All ants are in their nests at this stage. The surroundings don't contain any pheromones. The number of residual pheromones can be taken into account when designing algorithms without changing the likelihood.

Stage 2: The likelihood of the ants starting their search along each trail is the same (0.5). The curved route is obviously longer, requiring ants to go further to reach the food source.

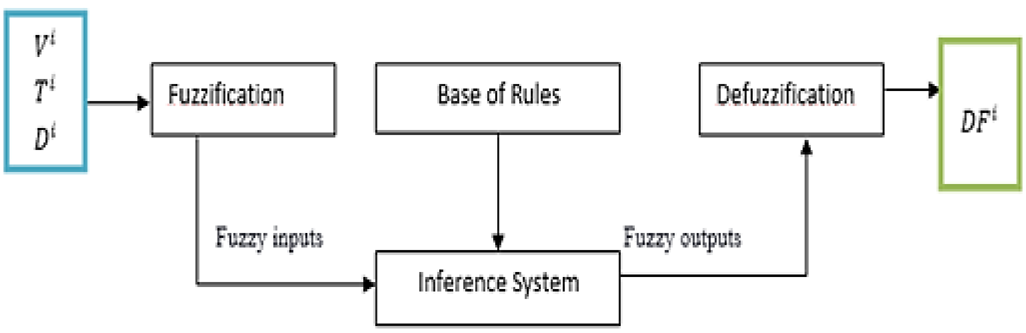

Fig. 2 Design of type-2 fuzzy logic method.

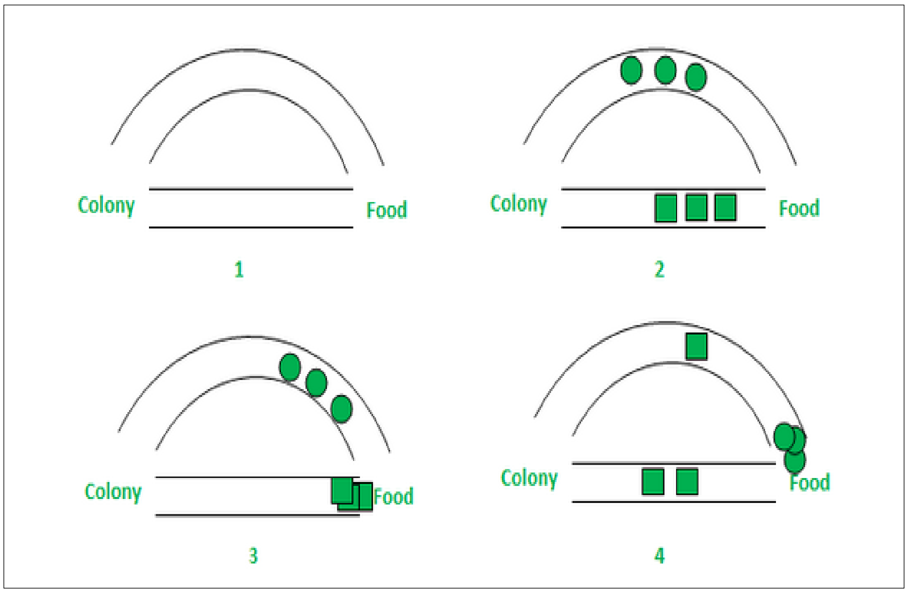

Fig. 3 Phases of ACO.

Stage 3: Due to the reduced distance, the ant colony reaches the food source faster. They now clearly meet the same selection issue, but this time selection is more likely as a result of the pheromone trail along the shorter, already-open path.
Stage 4: The shorter path is used by more ants, which causes the pheromone levels to rise. In addition, evaporation reduces the pheromone concentration along the longer path, which makes it less likely to be picked later. The entire colony eventually chooses the faster route with a higher probability. Therefore, path optimization is achieved.

3.3 Algorithmic design

It is now possible to create an algorithmic design because the ant's behavior has been established. To keep things simple, only two different ways to get from one ant colony to another have been researched. With the ant colony and the food source serving as the vertices (or nodes), the paths serving as the edges, and the pheromone concentrations serving as the weights applied to the edges, weighted graphs can be utilised to create the complete situation.

Let the graph be denoted by G = (V, E), with V and E acting as vertices and edges, respectively. According to our research, the vertices are Vs. Supply vertex, which symbolizes the ant colony, and the Vd Destination vertex, representing the food source. The lengths L1 and L2 of the two edges, E1 and E2, are, respectively. We may suppose that R1 and R2 are the corresponding pheromone values (indicating their intensities) for vertices E1 and E2, respectively. Use the following formula to calculate each ant's initial probability of path selection (between E1 and E2):

$$\mathrm{Pi} = \frac{\mathrm{Ri}}{\mathrm{R1+R2}}; \mathrm{i} = 1,2 \tag{1}$$

If R1>R2 and vice versa, selecting E1 is more likely. As soon as the user returns by this shortest way, let's say Ei, the pheromone value is changed for the pertinent path. An update is performed in accordance with the pheromone's rate of evaporation and the breadth of the paths. The actions that can be performed to implement the upgrade are listed below:
In accordance with path length –

$$\mathrm{Ri} \leftarrow \mathrm{Ri} + \frac{\mathrm{k}}{\mathrm{Li}} \tag{2}$$

The model's parameter in the aforementioned update is represented by the integers i = 1, 2, and "K." The length of the path also affects the updating. The amount of pheromone added increases with path length.
In accordance with the evaporation rate of pheromone –

$$\mathrm{Ri} \leftarrow (1-\nu) * \mathrm{Ri} \tag{3}$$

The 'v' parameter controls the pheromone evaporation and is part of the [0, 1] interval. I also equal 1 and 2.

3.4 The proposed ECFL-IoVT protocol

ECFL-IoVT is novel Emergency Communications using Fuzzy Logic for Internet of Vehicle Things (ECFL-IoVT).
ECFL-IoVT: For effective emergency data transmissions in VANETs connected to the Internet of Things, we proposed this protocol. The edge layer, fog layer, and cloud storage layer are just a few of the various layers that make up IoT-enabled VANETs.

- The RSUs or Gateway nodes' periodic data will be kept in the cloud storage layer for later analysis and decision-making.
- Data from the edge layer is collected at the fog layer, where processing, storage, and network connectivity

resources are distributed. The amount of energy used is considerably decreased, the complexity of space and time is reduced, and the usefulness and performance of this data are increased.

● The routing protocol is crucial at the edge layer for performing V2V or V2I communications in emergencies. To periodically sense the traffic conditions and communicate with the intended destinations, the edge layer is made up of a set of vehicles, RSUs, and gateway nodes. Due to high mobility and network dynamics, constructing the route from a source to a destination node is a complex research problem for the VANET-assisted IoT edge layer.

ECFL-IoVT is another invention of this research. We design the hybrid fuzzy logic rule that selects the next reliable vehicle for data transmission through the rules evaluation towards the ambulance to inform about the currently available freeway. The systematic and robust rules will be designed by considering the various parameters such as mobility, congestion, queue quality *etc*. We will use the type-2 fuzzy logic system for this contribution. The implementation and evaluation of this contribution perform with state-of-art similar techniques.

Table 1 shows the working of the proposed ECFL-IoVT protocol where the vehicle speed, traffic at a node, and distance-based routes are constructed from each pair $sv - dv$. As showing in algorithm 1, the fitness function computed using three key parameters such as node velocity, node traffic, and distance parameters. getVelocity (N^i) function computes the velocity of i^{th} ant node as:

$$V^i = 1 - \left(\frac{mobility(N^i,t)}{150}\right) \tag{4}$$

where, $mobility(N^i, t)$ sends back the vehicle's current speed at time t.

For emergency data transmission, traffic awareness is also important, thus we included the traffic parameter of next node for fitness computation. getTraffic (N^i) returns the level of traffic of i^{th} ant node as:

$$T^i = \frac{recvACK(E,N^i)}{genHello(E,N^i)} \tag{5}$$

where, $recvACK(E, N^i)$ denotes the number of received ACK at current emergency data transmission node E and $recvHello(E, N^i)$ generates the number of HELLO packets from E to N^i.

The getDist (NV^i, N^i) computes the geographic distance between NV^i to N^i. Using their current network positions, the distance is calculated. The RSSI values give the locations. The $distance^i$ using the node's trust score N^i is computed as:

$$r^1 = getRSSI(NV^i) \tag{6}$$

$$r^2 = getRSSI(N^i) \tag{7}$$

$$D^i = 1 - \frac{|r^2 - r^1|}{\left(\frac{(X+Y/2)}{2}\right)} \tag{8}$$

where X and Y stand for the VANET network's height and width, respectively, and $distance^i$ between 0 and 1. The higher the D^i value of the node N^i better the chance of becoming the next forwarder node.

Each fuzzy input variable V^i, T^i, and D^i computed, and its results fall between 0 and 1. The method used to determine these trust characteristics for each vehicle is demonstrated by equations (1), (2), and (5). The membership functions for each fuzzy input are defined in Table 2 in accordance with that.

Table 1. Pseudocode for ECFL-IoVT.

Emergency Data Transmission using Fuzzy Logic
Inputs sv: emergency data transmission vehicles dv: corresponding destination vehicles nb: Set of neighbouring nodes temp: temperory Vehicle t: Current simulation time P: number of iterations RT: Initial pheromone value Output: Emergency Data Transmission
1. While (P) 2. For each sv 3. temp ← sv 4. sv discovers the neighbouring nodes nb 5. Broadcast RREQs 6. Received RREPs 7. For each RREP node $N^i \in nb$ 8. V^i ← getVelocity (N^i) 9. T^i ← getTraffic (N^i) 10. D^i ← getDist (NV^i, N^i) 11. DF^i ← type2fuzzy(V^i, T^i, D^i) 12. F(i) ← DF^i 13. End For 14. temp ← max (F) 15. If (temp ≠ dv) 15.1. Update RT 15.2. sv ← temp 15.3. Go to step 3 16. Else 16.1. Build reverse route 16.2. Update RT 16.3. Initiate data transmission 17. End if 18. End For 19. End While

Type-2 fuzzy decision-making block, using a foundation of rules from Table 3 to map fuzzy input sets to output sets. The 27 rules demonstrate that we allocated decreasing priorities order for V^i, T^i, and D^i in order to preserve network dependability. The inference model categorised the sensor node as one of the linguistic outputs such as best, good, and bad, as indicated in Table 3 in accordance with the linguistic variables of each parameter (given in Table 2) of the sensor node.

Table 2. Fuzzy input in FIS membership functions for speed, traffic, and distance.

Variable	low	medium	high
V^i	$V^i \leq 0.3$	$V^i > 0.3$ && $V^i < 0.7$	$V^i \geq 0.7$
Variable	low	medium	high
T^i	$T^i \leq 0.3$	$T^i > 0.3$ && $T^i < 0.7$	$T^i \geq 0.7$
Variable	far	average	near
D^i	$D^i \leq 0.3$	$D^i > 0.3$ && $D^i < 0.7$	$D^i \geq 0.7$

Table 3. Basic laws.

Rules	V^i	T^i	D^i	Fuzzy Output
1	low	low	far	bad
2	low	low	average	bad
3	low	low	near	bad
4	low	medium	far	bad
5	low	medium	average	good
6	low	medium	near	good
7	low	high	far	bad
8	low	high	average	good
9	low	high	near	good
10	medium	low	far	bad
11	medium	low	average	good
12	medium	low	near	good
13	medium	medium	far	good
14	medium	medium	average	good
15	medium	medium	near	good
16	medium	high	far	good
17	medium	high	average	good
18	medium	high	near	good
19	high	low	far	bad
20	high	low	average	good
21	high	low	near	good
22	high	medium	far	good
23	high	medium	average	good
24	high	medium	near	best
25	high	high	far	good
26	high	high	average	best
27	high	high	near	best

4. Evaluation methodology

We run comprehensive simulations and contrast the outcomes with those of DTIOT, DDP4V, RWDCSO, EDTA[42] to assess the efficiency and performance of ECFL-IoVT. We assess throughput, routing overhead, packet delivery ratio, average delay.

Network Scenarios

Table 4 In this scenario, number of nodes connected in a network at a time is varied and thus varying the number of connections, for evaluation of routing protocol ECFL-IoVT.

Table 4. Performance parameter.

Parameter	Scenario 1	Scenario 2
Vehicle Density	50,100,150,200,250,300	100
Ambulance Moving	5	5
Simulation Time	300 second	300 second
Mobility (Km/hr)	40 km/hr	45, 50, 55, 60, 65, 70
Routing Protocol	ECFL-IoVT,DDP4V,DTIOT,RWDCSO	ECFL-IoVT,DDP4V,DTIOT, RWDCSO
MAC	802.11p	802.11p
Propagation Model	Two-Ray Ground	Two-Ray Ground
Area	7050 × 7050	7050 × 7050
Mobility	Random Walk	Manhattan grid mobility model
Antenna	Omni Antenna	Omni Antenna
Traffic Model	CBR	CBR

4.1 Performance metrics

4.1.1 Average throughput

This measurement determines the total number of packets, or messages, that are delivered per second. Average throughput measured in Kbps is:

$$\mathrm{T} = \left(\frac{\mathrm{R}}{\mathrm{T}^2 - \mathrm{T}^1}\right) \times \left(\frac{8}{1000}\right) \tag{9}$$

R is the total number of full packets received at all destination nodes, T^2 is simulation stop time and T^1 simulation start time.

4.1.2 PDR

It involves calculating the proportion of packets transmitted by the various sources of the various traffic patterns and received by the destinations. The calculation is:

$$\mathrm{P} = \left(\frac{\mathrm{P_r}}{\mathrm{P_g}}\right) \times 100 \tag{10}$$

Where, P_r is the number of packets that were received and P_g is the total number of packets produced.

4.1.3 Average delay

It is calculated as the proportion of total network data packets to total routing packets. It's calculated as:

$$\mathrm{O} = \sum_t \left(\frac{\mathrm{RT^t}}{\mathrm{DT^t}}\right) \tag{11}$$

where, RT^t is the overall quantity of routing packets and DT^t

contains all data packets at time t.

4.1.4 Communication Delay: The average amount of time between the time a packet leaves all sources and arrives at all destination nodes is determined by this measure. It is calculated as:

$$D = \frac{\sum_{i=1}^{N} \quad d_t^i + d_p^i + d_{pc}^i + d_q^i}{N} \tag{12}$$

N is the total number of transmission links, d_t^i is delay in transmission of i^{th}link, d_p^i is delayed propagation of i^{th}link, d_{pc}^i is delays in processing of i^{th} link, and d_q^i is delay in transmission of i^{th}link.

5. Result and discussion

5.1 An evaluation of the simulation's settings based on the changing number of vehicles

This section analyses the average throughput, packet delivery rate, communication overhead, and average latency metrics in relation to the number of cars. The comparisons of this protocol's 50, 100, 150, 200, 250, and 300 nodes' test results and findings are satisfactory. The intended results are still generated despite the increasing number of cars, as seen in Figs. 4, 5, 6, and 7, demonstrating the scalability of the suggested procedure.

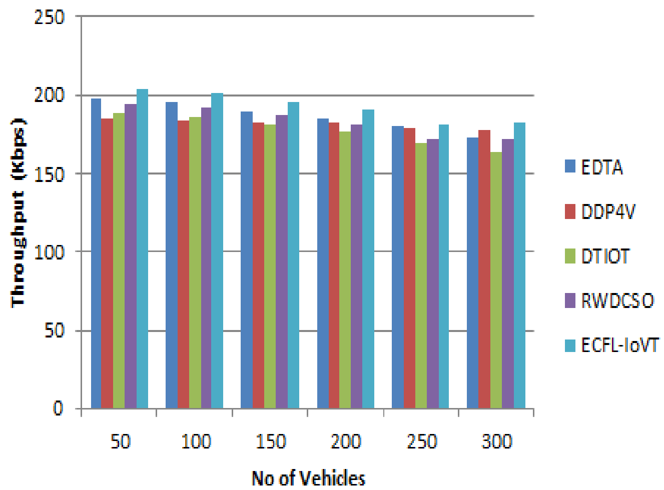

Fig. 4 Throughput based on number of vehicles.

5.1.1 Average throughput

Figure 4 shows a throughput performance comparison between ECFL-IoVT and EDTA, DDP4V, DTIOT, and RWDCSO. According to simulation results, ECFL-IoVT performed better than the other four procedures. In contrast, EDTA, DDP4V, DTIOT, and RWDCSO employ ACO and take longer to converge, making it more difficult to choose the best route.

5.1.2 PDR

Figure 5 shows a comparison of the effectiveness of ECFL-IoVT for packet delivery ratio with EDTA, DDP4V, DTIOT, and RWDCSO. The ECFL-IoVT protocol's fuzzy logic idea and the intelligent setting of fitness function parameters like velocity, traffic, and distance are to blame for this increase. These factors have a favourable impact on the data packet delivery ratio by encouraging the use of more stable routes as the best option. ECFL-IoVT outperforms DDP4V, DTIOT, and RWDCSO in terms of PDR: PDR for AODV, RPSPF, VACO, and EDTA, according to simulation data.

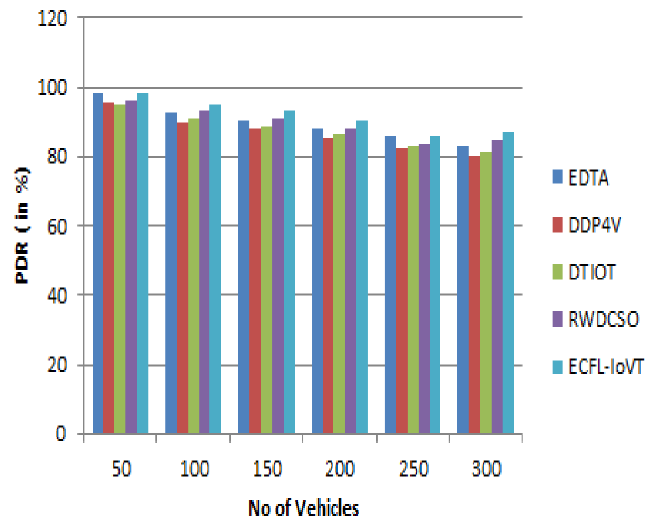

Fig. 5 Packet delivery ratio based on the number of vehicles.

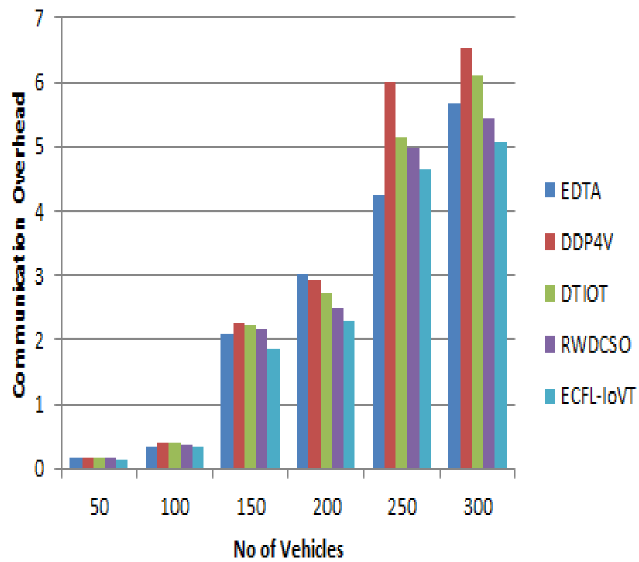

Fig. 6 Communication overhead based on number of vehicles.

5.1.3 Communication overhead

Figure 6 shows the communication overhead values for the various car counts for the ECFL-IoVT, EDTA, DDP4V, DTIOT, and RWDCSO. While other routing protocols carry out this phase with extra system overhead, ECFL-IoVT controls the discovery phase without broadcasting route request control packets. Due to the use of the ACO metaheuristic algorithm, fuzzy logic notion, and storing of all of the colony's data, other routing protocols place a burden on the system as well. ECFL-IoVT outperforms other protocols in terms of produced overhead. Fig. 6 shows how the communication overhead increases as the number of vehicles increases.

5.1.4 Average delay

The average delay also rises as the number of vehicles increases. When the ACO algorithm and the fuzzy logic idea are applied to the ECFL-IoVT protocol, the optimum route can be chosen faster than with the other four protocols. In contrast to EDTA, which converges slowly because of the ant colony optimisation algorithm (ACO), ECFL-IoVT converges quickly and can find the best route more quickly. Additionally, this protocol's fitness function's intelligent setup and consideration of variables like the available buffer have proven to be highly helpful in the deselection of crowded routes. Fig. 7 illustrates how choosing less congested routes has reduced average delays.

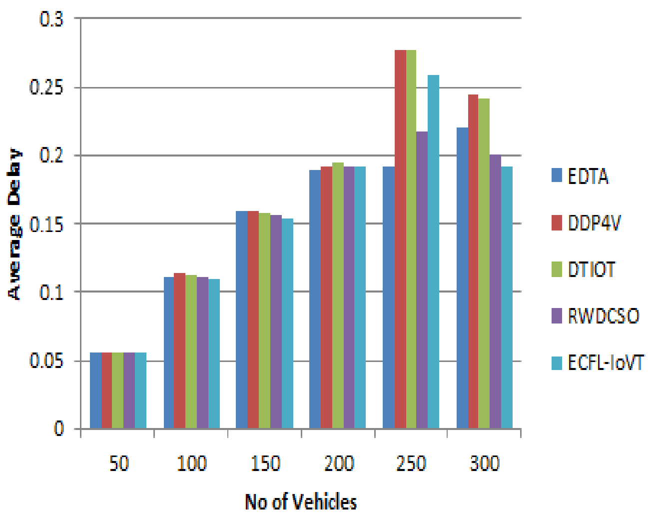

Fig. 7 Average delay based on number of vehicles.

5.2 On the basis of the variable speed in km/hr, an evaluation of the simulation's parameters

This section analyses the average throughput, packet delivery rate, communication overhead, and average latency metrics in relation to the number of cars. The comparisons and test findings between 45, 50, 55, 60, 65, and 70 km/hr vehicle speed were adequate in this procedure. The intended outcomes are still generated despite the increasing number of cars, as seen in Figs. 8, 9, 10, and 11, demonstrating the scalability of the suggested procedure.

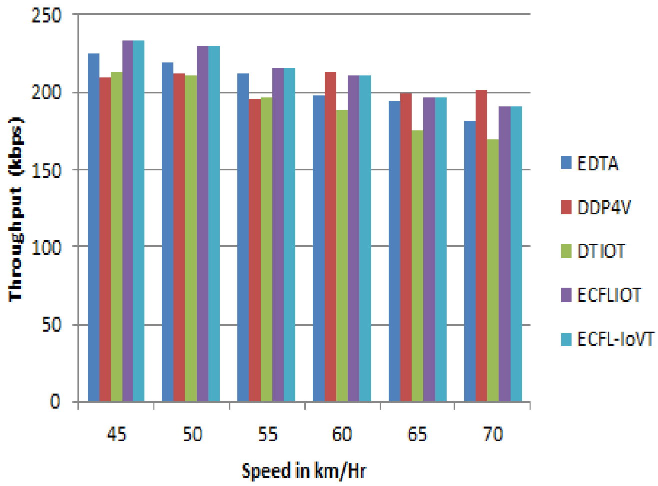

Fig. 8 Throughput based on speed km/Hr.

5.2.1 Average throughput

A comparison of the throughput capacities of the ECFL-IoVT, EDTA, DDP4V, DTIOT, and RWDCSO results from the simulation show that the ECFL-IoVT fared better than the other four protocols. Also, as compared with Fig. 4, the average throughput increased, as shown in Fig. 8. The throughput for the variable number of vehicles with the fixed speed is less than the throughput for the same number of vehicles with a different speed. From Fig. 8, it is clear that as the speed increases, the throughput decreases.

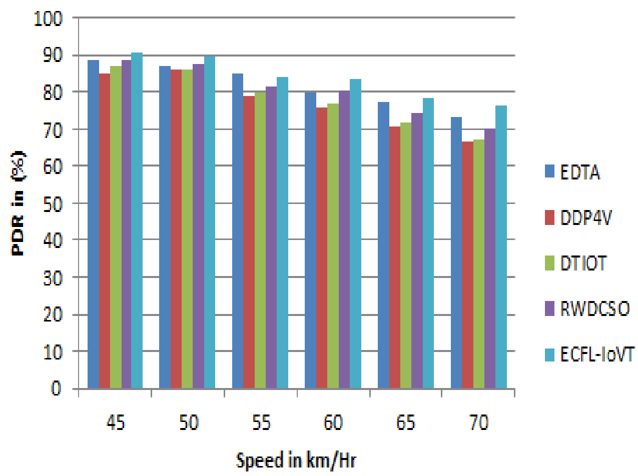

Fig. 9 Packet delivery ratio based on speed km/Hr.

5.2.2 PDR

Comparison of the performance of ECFL-IoVT with that of EDTA, DDP4V, DTIOT, and RWDCSO for packet delivery ratio This improvement is due to the fuzzy logic concept in the ECFL-IoVT protocol and the intelligent configuration of the fitness function parameters such as velocity, traffic, and distance, which positively affect the data packet delivery ratio via the selection of more stable routes as the optimal route. From Fig. 5 and Fig. 9, it is clear that the packet delivery ratio is greater with the fixed speed. If the speed of the vehicle is variable, then the packet delivery ratio is reduced as compared with a fixed speed.

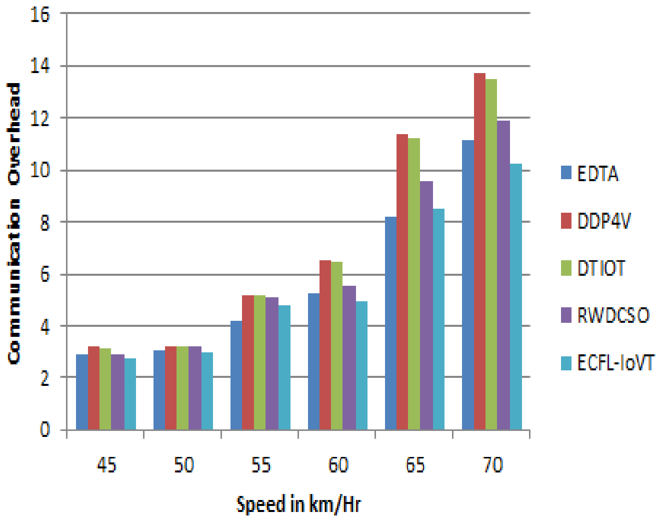

Fig. 10 Communication overhead based on speed km/Hr.

5.2.3 Communication overhead

The communication overhead values of ECFL-IoVT, EDTA, DDP4V, DTIOT and RWDCSO for various numbers of vehicles. As the speed is increses the communication overhead is also increases gradually.It is greater than the fix speed along with variable number of vehicles as shown in Fig. 6.

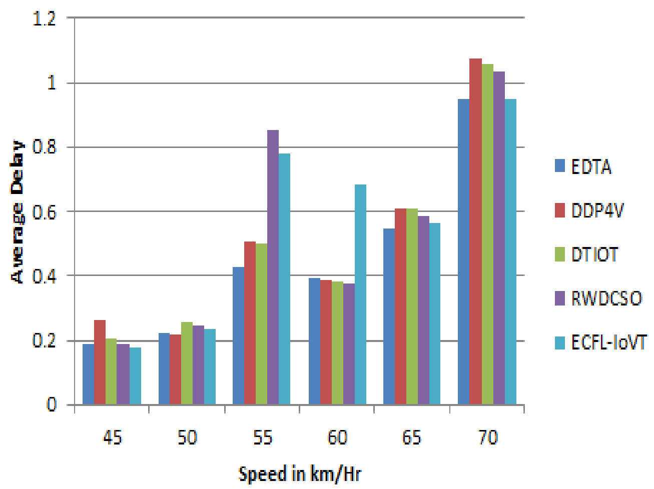

Fig. 11 Average delay based on speed km/Hr.

5.2.4 Average delay

When the number of vehicles increases, average delay also increases. Applying the ACO algorithm along with fuzzy logic concept to ECFL-IoVT has helped in the selection of the best route in a shorter time than the other four protocols. In contrast with Fig. 7, Fig. 9 shows that the delay is also reduced.

6. Conclusion

Ad hoc networks with a specialisation in VANETs are made up of nodes connected by wireless links that lack any fixed infrastructure. In these networks, efficient routing has become a serious difficulty due to this and the absence of a centralised administration. In this paper, we propose the ECFL-IoVT routing protocol for VANETs. This protocol made intelligent use of fuzzy logic and ant colony optimisation. In ECFL-IoVT, the fuzzy logic system is utilised to restrict the route discovery phase, and by restricting the route request messages, it partly regulates the generated extra overhead.

The three variables of velocity, traffic, and distance are the inputs for the fuzzy logic system. The ACO algorithm is invoked after determining the routes in the source node. One of the most successful bioinspired algorithms, particularly in the broad search area, is this one. By computing the fitness function based on factors like velocity, traffic, and distance, it chooses the most stable and ideal route out of all the known routes.

According to the findings of the simulation, ECFL-IoVT outperformed EDTA, DDP4V, DTIOT, and RWDCSO in terms of average throughput, packet delivery ratio, communication overhead, and average delay. It is feasible to choose a path that is more stable using the fitness function's velocity parameter, traffic parameter, and distance. Along with the available buffers, these characteristics can boost the delivery rate of data packets. Because it uses the ACO algorithm and its distinctive properties, such as fitness function, which is distribution in this algorithm, ECFL-IoVT is suggested to be superior than the EDTA protocol employed by the ant colony algorithm.

Acknowledgements

I might want to communicate my extremely incredible gratefulness to Dr. Uma Pujeri for her valuable and useful recommendations during an arranging and improvement of this exploration work. Her eagerness to give her time so liberally has been very much appreciated.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

References

[1] S. Singh, S. Agrawal, VANET routing protocols: issues and challenges, 2014 Recent Advances in Engineering and Computational Sciences (RAECS). Chandigarh, India. IEEE, 2014, 1-5, doi: 10.1109/RAECS.2014.6799625.

[2] H. Fatemidokht, M. Kuchaki Rafsanjani, F-Ant: an effective routing protocol for ant colony optimization based on fuzzy logic in vehicular ad hoc networks, *Neural Computing and Applications*, 2018, **29**, 1127-1137, doi: 10.1007/s00521-016-2631-y.

[3] S. Dehghani, M. Pourzaferani, B. Barekatain, Comparison on energy-efficient cluster based routing algorithms in wireless sensor network, *Procedia Computer Science*, 2015, **72**, 535-542, doi: 10.1016/j.procs.2015.12.161.

[4] S. Dehghani, B. Barekatain, M. Pourzaferani, An enhanced energy-aware cluster-based routing algorithm in wireless sensor networks, *Wireless Personal Communications*, 2018, **98**, 1605-1635, doi: 10.1007/s11277-017-4937-1.

[5] S. Bitam, A. Mellouk, S. Zeadally, Bio-inspired routing algorithms survey for vehicular ad hoc networks, *IEEE Communications Surveys & Tutorials*, 2015, **17**, 843-867, doi: 10.1109/COMST.2014.2371828.

[6] H. Rana, P. Thulasiraman, R. K. Thulasiram, MAZACORNET: mobility aware zone based ant colony optimization routing for VANET, 2013 IEEE Congress on Evolutionary Computation. Cancun, Mexico. IEEE, 2013, 2948-2955, doi: 10.1109/CEC.2013.6557928.

[7] S. Al-Sultan, M. M. Al-Doori, A. H. Al-Bayatti, H. Zedan, A comprehensive survey on vehicular Ad Hoc network, *Journal of Network and Computer Applications*, 2014, **37**, 380-392, doi: 10.1016/j.jnca.2013.02.036.

[8] C. Wu, S. Ohzahata, T. Kato, Routing in VANETs: a fuzzy constraint Q-Learning approach, 2012 IEEE Global Communications Conference (GLOBECOM). Anaheim, CA, USA. IEEE, 2012, 195-200, doi: 10.1109/GLOCOM.2012.6503112.

[9] K. N. Qureshi, A. H. Abdullah, A. Altameem, Road aware geographical routing protocol coupled with distance, direction and traffic density metrics for urban vehicular ad hoc networks, *Wireless Personal Communications*, 2017, **92**, 1251-1270, doi: 10.1007/s11277-016-3604-2.

[10] B. Barekatain, D. Khezrimotlagh, M. A. Maarof, A. A. Quintana, A. T. Cabrera, GAZELLE: an enhanced random network coding based framework for efficient P2P live video streaming over hybrid WMNs, *Wireless Personal Communications*, 2017, **95**, 2485-2505, doi: 10.1007/s11277-016-3930-4.

[11] N. V. Dharani Kumari, B. S. Shylaja, AMGRP: AHP-based Multimetric Geographical Routing Protocol for Urban environment of VANETs, *Journal of King Saud University - Computer and Information Sciences*, 2019, **31**, 72-81, doi: 10.1016/j.jksuci.2017.01.001.

[12] T.-Y. Wu, Y.-B. Wang, W.-T. Lee, Mixing greedy and predictive approaches to improve geographic routing for VANET, *Wireless Communications and Mobile Computing*, 2012, **12**, 367-378, doi: 10.1002/wcm.1033.

[13] B. Barekatain, D. Khezrimotlagh, M. A. Maarof, H. R. Ghaeini, A. A. Quintana, A. T. Cabrera, Efficient P2P live video streaming over hybrid WMNs using random network coding, *Wireless Personal Communications*, 2015, **80**, 1761-1789, doi: 10.1007/s11277-014-2112-5.

[14] B. Barekatain, D. Khezrimotlagh, M. Aizaini Maarof, H. R. Ghaeini, S. Salleh, A. A. Quintana, B. Akbari, A. T. Cabrera, MATIN: A random network coding based framework for high quality peer-to-peer live video streaming, *PLoS One*, 2013, **8**, e69844, doi: 10.1371/journal.pone.0069844.

[15] B. Barekatain, Performance evaluation of routing protocols in live video streaming over wireless mesh networks, *Jurnal Teknologi*, 2013, **62**, 85-94, doi: 10.11113/jt.v62.1495.

[16] B. Barekatain, M. A. Maarof, A. A. Quintana, A. T. Cabrera, GREENIE: a novel hybrid routing protocol for efficient video streaming over wireless mesh networks, *EURASIP Journal on Wireless Communications and Networking*, 2013, **2013**, 168, doi: 10.1186/1687-1499-2013-168.

[17] G. Li, M. Ma, C. Liu, Y. Shu, Adaptive fuzzy multiple attribute decision routing in VANETs, *International Journal of Communication Systems*, 2017, **30**, e3014, doi: 10.1002/dac.3014.

[18] P. Sermpezis, G. Koltsidas, F.-N. Pavlidou, Investigating a junction-based multipath source routing algorithm for VANETs, *IEEE Communications Letters*, 2013, **17**, 600-603, doi: 10.1109/LCOMM.2013.011513.122045.

[19] L. N. Balico, H. A. B. F. Oliveira, R. S. Barreto, A. A. F. Loureiro, R. W. Pazzi, A prediction-based routing algorithm for Vehicular Ad Hoc Networks, 2015 IEEE Symposium on Computers and Communication (ISCC). Larnaca, Cyprus. IEEE, 2015, 365-370, doi: 10.1109/ISCC.2015.7405542.

[20] J.-M. Chang, C.-F. Lai, H.-C. Chao, R. Zhu, An energy-efficient geographic routing protocol design in vehicular ad-hoc network, *Computing*, 2014, **96**, 119-131, doi: 10.1007/s00607-012-0235-7.

[21] C. Wu, S. Ohzahata, T. Kato, Flexible, portable, and practicable solution for routing in VANETs: a fuzzy constraint Q-learning approach, *IEEE Transactions on Vehicular Technology*, 2013, **62**, 4251-4263, doi: 10.1109/TVT.2013.2273945.

[22] E. Moridi, H. Barati, RMRPTS: a reliable multi-level routing protocol with tabu search in VANET, *Telecommunication Systems*, 2017, **65**, 127-137, doi: 10.1007/s11235-016-0219-6.

[23] S. Bitam, A. Mellouk, S. Zeadally, HyBR: A Hybrid Bio-inspired Bee swarm Routing protocol for safety applications in Vehicular Ad hoc NETworks (VANETs), *Journal of Systems Architecture*, 2013, **59**, 953-967, doi: 10.1016/j.sysarc.2013.04.004.

[24] H. Dong, X. Zhao, L. Qu, X. Chi, X. Cui, Multi-hop routing optimization method based on improved ant algorithm for vehicle to roadside network, *Journal of Bionic Engineering*, 2014, **11**, 490-496, doi: 10.1016/S1672-6529(14)60061-5.

[25] B. Barekatain, S. Dehghani, M. Pourzaferani, An energy-aware routing protocol for wireless sensor networks based on new combination of genetic algorithm & k-means, *Procedia Computer Science*, 2015, **72**, 552-560, doi: 10.1016/j.procs.2015.12.163.

[26] M. Al-Rabayah, R. Malaney, A new scalable hybrid routing protocol for VANETs, *IEEE Transactions on Vehicular*

Technology, 2012, **61**, 2625-2635, doi: 10.1109/TVT.2012.2198837.
[27] L. A. Zadeh, Fuzzy sets, *Information and Control*, 1965, **8**, 338-353, doi: 10.2307/2272014.
[28] L. Altoaimy, I. Mahgoub, Fuzzy logic based localization for vehicular ad hoc networks, 2014 IEEE Symposium on Computational Intelligence in Vehicles and Transportation Systems (CIVTS). Orlando, FL, USA. IEEE, 2014, 121-128, doi: 10.1109/CIVTS.2014.7009487.
[29] X.-S. Yang, S. Deb, Cuckoo Search via Lévy flights, 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC). Coimbatore, India. IEEE, 2009, 210-214, doi: 10.1109/NABIC.2009.5393690.
[30] A. I. Saleh, S. A. Gamel, K. M. Abo-Al-Ez, A reliable routing protocol for vehicular ad hoc networks, *Computers & Electrical Engineering*, 2017, **64**, 473-495, doi: 10.1016/j.compeleceng.2016.11.011.
[31] K. Mehta, P. R. Bajaj, L. G. Malik, Fuzzy Bacterial Foraging Optimization Zone Based Routing (FBFOZBR) protocol for VANET, 2016 International Conference on ICT in Business Industry & Government (ICTBIG). Indore, India. IEEE, 2016, 1-10, doi: 10.1109/ICTBIG.2016.7892669.
[32] C. E. Perkins, E. M. Royer, Ad-hoc on-demand distance vector routing, Proceedings WMCSA'99. Second IEEE Workshop on Mobile Computing Systems and Applications. New Orleans, LA, USA. IEEE, 2002, 90-100, doi: 10.1109/MCSA.1999.749281.
[33] A. Feyzi, V. Sattari-Naeini, Application of fuzzy logic for selecting the route in AODV routing protocol for vehicular ad hoc networks, 2015 23rd Iranian Conference on Electrical Engineering. Tehran, Iran. IEEE, 2015, 684-687, doi: 10.1109/IranianCEE.2015.7146301.
[34] T. Hu, M. Liwang, L. Huang, Y. Tang, An enhanced GPSR routing protocol based on the buffer length of nodes for the congestion problem in VANETs, 2015 10th International Conference on Computer Science & Education (ICCSE). Cambridge, UK. IEEE, 2015, 416-419, doi: 10.1109/ICCSE.2015.7250281.
[35] X.-B. Wang, Y.-L. Yang, J.-W. An, Multi-metric routing decisions in VANET, 2009 Eighth IEEE International Conference on Dependable, Autonomic and Secure Computing. Chengdu, China. IEEE, 2009, 551-556, doi: 10.1109/DASC.2009.37.
[36] X.-A. Li, C. Chen, Z. Wang, L. Liu, J. Lv, An adaptive geographic routing protocol based on quality of transmission in urban VANETs, 2018 IEEE International Conference on Smart Internet of Things (SmartIoT). Xi'an, China. IEEE, 2018, 52-57, doi: 10.1109/SmartIoT.2018.00019.
[37] N. Li, J.-F. Martinez-Ortega, V. H. Diaz, J. A. S. Fernandez, Probability prediction-based reliable and efficient opportunistic routing algorithm for VANETs, *ACM Transactions on Networking*, 2018, **26**, 1933-1947, doi: 10.1109/tnet.2018.2852220.
[38] H. Bello-Salau, A. J. Onumanyi, A. M. Abu-Mahfouz, A. O. Adejo, M. B. Mu'Azu, New discrete cuckoo search optimization algorithms for effective route discovery in IoT-based vehicular ad-hoc networks, *IEEE Access*, 2020, **8**, 145469-145488, doi: 10.1109/ACCESS.2020.3014736.
[39] S. Latif, S. Mahfooz, N. Ahmad, B. Jan, H. Farman, M. Khan, K. Han, Industrial Internet of Things based efficient and reliable data dissemination solution for vehicular ad hoc networks, *Wireless Communications and Mobile Computing*, 2018, **2018**, 1857202, doi: 10.1155/2018/1857202.
[40] Muhammad Asim Saleem, Zhou Shijie, Abida Sharif, Data Transmission Using IoT in Vehicular Ad-Hoc Networks in Smart City Congestion,Mobile Networks and Applications, Springer, 10 January 2019, 1-11.
[41] C. Hemant Nemade, U. Pujeri, Comparative study and performance analysis of MANET routing protocol, *International Journal of Electrical and Computer Engineering Systems*, 2023, **14**, 145-154, doi: 10.32985/ijeces.14.2.4.
[42] C. H. Nemade, U. Pujeri, Emergency automobile data transmission with ant colony optimization (ACO), *Journal of Advances in Information Technology*, 2023, **14**, 1003-1011, doi: 10.12720/jait.14.5.1003-1011.
[43] C. H. Nemade, U. Pujeri, A study on different movement the executives plan for emergency automobile utilizing various logarithms, *Psychology and Education*, 2020, **57**, 1726-1731, doi: 10.17762/pae.v57i9.522.
[44] G. Pugalendhi, D. Velusamy, A. Paul, K.-J. Kim, Fuzzy-based trusted routing to mitigate packet dropping attack between data aggregation points in smart grid communication network, *Computing*, 2017, **99**, 81-106, doi: 10.1007/s00607-016-0518-5.
[45] R. R. Rout, S. Vemireddy, S. K. Raul, D. V. L. N. Somayajulu, Fuzzy logic-based emergency vehicle routing: an IoT system development for smart city applications, *Computers & Electrical Engineering*, 2020, **88**, 106839, doi: 10.1016/j.compeleceng.2020.106839.
[46] J. Shi, J. Wu, A. Paul, L. Jiao, M. Gong, Change detection in synthetic aperture radar images based on fuzzy active contour models and genetic algorithms, *Mathematical Problems in Engineering*, 2014, **2014**, 870936, doi: 10.1155/2014/870936.
[47] H. Li, H. Wu, I. Gulati, S. A. Ali, V. Pickert, S. Dlay, An improved sliding mode control (SMC) approach for enhancement of communication delay in vehicle platoon system, *IET Intelligent Transport Systems*, 2022, **16**, 958-970, doi: 10.1049/itr2.12189.
[48] H. Li, I. Gulati, S. Stainton, S. A. Ali, V. Pickert, S. Dlay, Sliding Mode Control for Vehicular Platoon based on V2V Communication, Proceedings of the 32nd International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2019)", 2019, 2078-2089, doi: 10.33012/2019.16887.

Publisher's Note: Engineered Science Publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

