Tuijin Jishu/Journal of Propulsion Technology
ISSN:1001-4055
Vol. 44 No.2 (2023)

Balancing Security and Energy-Efficiency in Vehicular Ad-Hoc Sensor Networks Using EHDSORP

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Abstract

Automobile networks have been the focus of growing amounts of research from scholarly community and organization as a method to improve traffic safety and provide drivers and passengers with real-time data. Beyond that, however, what is driving the expansion of VANETs is the need for a safe and secure network in moving vehicles. Ad hoc vehicular networks are made up of intelligent, on-the-road cars that can exchange data with one other and with permanent roadside infrastructure. In order to provide an energy-efficient and secure routing for ad-hoc sensor networks, a balancing security-based energy-aware routing leveraging the hybrid Fuzzy logic technique with dove swarm optimization-based routing (HFLDSOR) protocol is proposed in this study. The sensor nodes in this balancing security-based energy-aware routing are first set up in the ad hoc network. The clustering is carried out using an estimate of the distance between each node, and the cluster head (CH) is chosen using a fuzzy logic method. After the selection of the CH, the distance between each node, the quantity of energy left, and the number of neighbours for each node are evaluated as fuzzy logic criterion. In order to choose the best routing route for secured communication, the trustworthy nodes are forwarded. Balancing security-based hybrid vehicles that use less energy The optimum paths to the target are chosen using fuzzy logic method with dove swarm optimization-based routing (SE- HFLDSOR) protocol approach based on the parameters such as distance delay and energy objective function. Consequently, the SE- HFLDSOR protocol was used for safe and energy-efficient routing. The suggested model outperforms the comparable current procedures, according to the assessment performed using the MATLAB simulation tool. Hence, the SE-HFLDSOR protocol was appropriate for real-time applications.

Keywords: *VANETs, Residual energy and trust evaluation, Energy consumption, Routing algorithm, Fuzzy logic and DSO.*

1. Introduction

In urban and highway contexts, VANET, a particular kind of mobile ad hoc network (MANET), is leveraging to facilitate communications between automotive nodes. Vehicle, driver, and passenger-related VANET applications include traffic control, security, highway safety, information services, entertainment, accident alert, and cooperative driving. Many issues that VANETs must deal with include rivalry, interference, poor channels, high vehicle mobility, fast topology changes, and restricted geographic positioning and movement directions [1, 2]. It is believed that VANETs are a good option and a crucial component in the development of intelligent transportation systems (ITSs). This communication system facilitates data transmission, internet access, and traffic congestion detection. global positioning system (GPS) is used by VANET to determine the geographic location of nodes [3]. Because of the nodes' great mobility inside the VANET network, the topology is constantly changing. It is an arrangement of swiftly moving, extremely mobile vehicles. Making vehicles clever enough to communicate among themselves without human intervention is the primary goal of the VANET. VANET construction is shown in Fig. 1 [4].

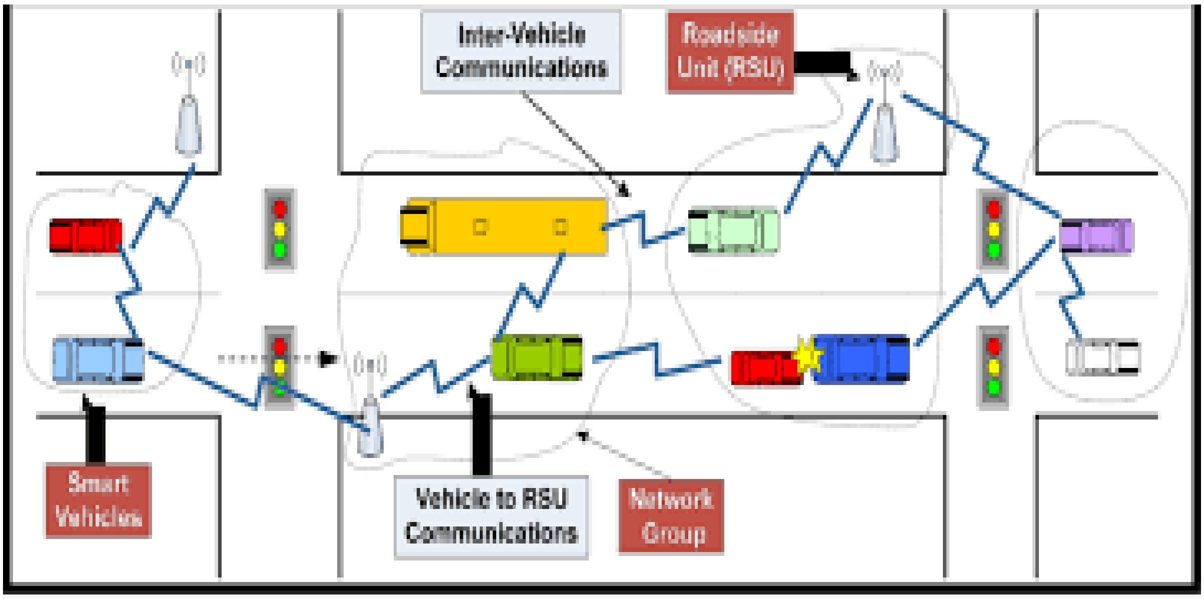


Fig.1: Structure of VANET

Due to the fact that vehicular nodes may collect geographic coordinates through onboard global positioning system (GPS) receivers, position-based routing protocol is thought to be a particularly advantageous routing technique for data transfer inside VANETs. Moreover, vehicle nodes may get information on global road outlines from an onboard digital map when using the position-based routing protocol [5-7]. Position-based routing systems often use greedy forwarding and are suitable for VANETs because of their highly dynamic and rapidly changing network architecture. The key benefits of position-based routing protocol are scalability, efficiency in dynamically changing mobility patterns, and minimal overhead [8,9].

Routing problems including the high mobility of vehicles, frequent route failures, blind packet propagation, and bandwidth restrictions in VANET enhance frequent route disconnections, add overhead, and reduce routing process efficiency [10–12]. The VANET network became very dynamic as a consequence of the vehicle's high degree of mobility, and the movement of the intermediary vehicles led to frequent data transmission disconnections. The network topology often changes as a result of the vehicle's rapid mobility [13]. The numerous route failures caused by network changes on a regular basis have a significant impact on VANET routing. After a route break, overhead rises due to the reconstruction of the routes. Because of the high mobility and sporadic joining/leaving of cars in the VANET, changes take place in an unexpected way. Regular route breaks occur along the route between the origin and the objective as a result of irregular changes [15]. The route discovery method uses more control packets and generates overhead as a consequence of the blind propagation of route request packets [15, 16]. The routing procedure is inefficient as a result of the significant overhead. In VANET, the radio band is constrained. Due to this restriction, network routing must make optimum use of available bandwidth while maintaining minimal overhead. More bandwidth is used by the unstable long route, which ultimately leads to significant control overhead and bandwidth waste [17, 18].

Ad-Hoc on-demand distance vector (AODV), dynamic source routing (DSR), destination-sequenced distance vector (DSDV), and other conventional routing protocols are appropriate for VANETs. Previous studies have shown that AODV is the most effective classical routing system for establishing optimal paths for data transport [19]. Due to the high degree of vehicle movement, communication connections in VANETs are often lost, making conventional routing techniques useless. Geographic location-based routing, map-based routing, location and route-based routing, and topography-based routing have all been the subject of recent study. High vehicle mobility in VANETs causes dynamic topology changes, which are reflected in quick channel changes and frequent handovers. These factors make it crucial to evaluate and forecast vehicle trajectory. For the development of routing algorithms for VANETs, swarm intelligence algorithms that mimic the group behaviour of various birds in nature, such as crumbs, have been proposed. In this study, we provide an improved framework for vehicular ad hoc networks' hybrid dove swarm optimization routing protocol based on fuzzy logic, which may offer a high data packet delivery ratio and low end-to-end latency.

Contribution of the Research

- This researchpresents a novel balancing security-based energy efficient (HFLDSOR) hybrid Fuzzy logic technique with dove swarm optimization-based routing, called SE- HFLDSOR protocol for VANET.
- The presented SE-HFLDSOR technique initially, enables communication between the vehicles.
- The Fuzzy logic technique effectively chooses CHs and assembles clusters leveraging node degree, distance, and residual energy as input parameters.
- Improving network efficiency with regard to package transfer speed and delay reduction.
- Moreover, the DSO method is used in conjunction with a fitness function for selecting the best possible inter-cluster communication pathways.
- The performance of the projected technique is analysed with various metrices using MATLAB platform. The proposed SE- HFLDSOR protocol is compared with the conventional techniques such as Recurrent Neural Network- Particle Swarm Optimization (RNN-PSO), RNN-DOA (Recurrent Neural Network Dragonfly Optimization Algorithm) and Recurrent Neural Network -COOT respectively.

The remains of the article are structured as follows. Related work is included in Section 2. The proposed work's technique is presented in Section 3. The performance of the proposed approach is outlined in Section 4. The intended work is concluded in Section 5.

2. Recent review

In the literature, a number of researchers performed performance assessments of different routing protocols in VANETs in relation to a number of performance criteria.

An AODV and Ant Colony Optimization (ACO) approach has been described by Sindhwaniet al. and is used to transport data. The ant colony optimization technique is used, taking each node's starting coordinates into account. Reactive routing protocol-established paths are more likely to experience network congestion and use up a lot of available bandwidth. The goal of that effort is to construct a multicasting-based route from source to destination while simultaneously lowering the likelihood of network congestion.

To get the messages to the intended location, Kachooeiet al. looked into a table-driven Optimized Link State Routing (OLSR) protocol. We suggest many improvements to message flows and data exchanges to adapt the OLSR protocol for geocasting. OLSR enforces a smaller message delay and sends more messages to the target area at a greater overhead cost than on-demand geocast protocols. A Hybrid Genetic Firefly Algorithm-based Routing Protocol (HGFA) has been introduced byDafalla, Mohammed ElaryhMakki and is quicker communication in VANET. Both sparse network scenarios and dense network scenarios may use features of the Genetic Algorithm (GA) that are linked with the Firefly algorithm for VANET routing.

Reliability Aware Multi-Objective Optimization (RAMO) Based VANETs Routing was introduced by Khezri, Edris, EsmaeilZeinali, and HadiSargolzaey. The framework consists of three levels: the simulation of the VANET system is at level 1, the routing criteria are at level 2, and the routing algorithm is at level 3. The next step is the real network. The framework also has an optimization block, which regulates the reliability, geometrical, and routing blocks' characteristics. The optimization is based on the creation of a unique multi-objective harmony seeking variation and is given from a multi-objective viewpoint. This technique, called Improved Gaussian Mutation Harmony Searching (EGMHS), combines objective decomposition, harmony memory extraction, and Gaussian mutation.

To improve the functionality of OLSR in VANETs, Yang et al. have introduced a multi-objective particle swarm optimization (MOPSO) framework. We specifically define a multi-objective optimization problem (MOP) taking into account both the cost of service, or routing burden, as well as the quality of service (QoS), which includes throughput, latency, and packet loss rate. We use MOPSO to solve this MOP, and the result is the Pareto front that corresponds to the best performance/cost equilibrium.

3. The proposed SE- HFLDSOR protocol

The general operating process for the proposed hybrid Fuzzy logic technique with dove swarm optimization-based routing (HFLDSOR) technology is shown in figure 2. The vehicles are positioned in the network and have already begun communicating with one another, as shown in the figure. The FL approach is then used to choose CHs and build clusters by connecting neighbouring nodes to CHs in the next step. Also, the optimal collection of inter-cluster communication channels is selected using the DSOR method. The data will finally start to be sent through inter-cluster communication from cluster members (CMs) to CHs and then to Base Station (BS).

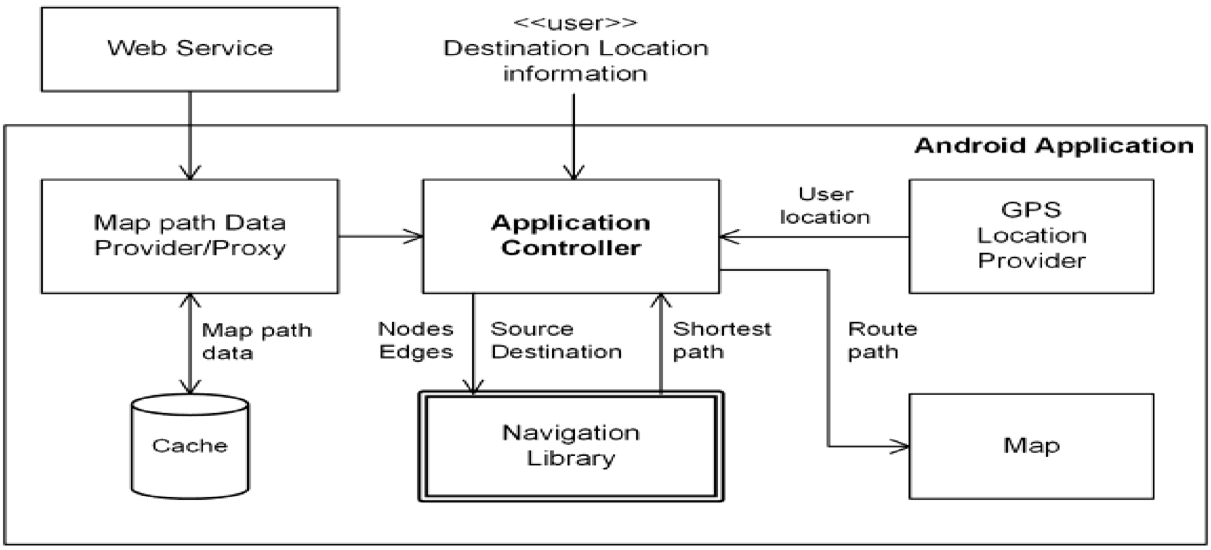


Fig.2: Architecture of proposed SE-HFLDSOR model

3.1. Fuzzy Logic based clustering technique

The important aim of communications in a VANET is message routing, and they take place across a multi-hop between the source and destination nodes. A path is built across several moving vehicles during runtime. A device travels out of a route and out of another device's communication range, and the route connections are broken. The vehicles transmit and receive control packets in order to establish and maintain the routes. The quality of service in VANETs will be significantly impacted by an increase in these packet numbers. This protocol's first phase, which focuses on the fuzzy logic system, transmits packet requests in a targeted manner to a number of chosen adjacent nodes. Based on the presence of certain characteristics, this portion of the nearby nodes was chosen. The fuzzy logic system accepts these attributes as inputs. The FL is used to collect statistics on vehicles that convert to CHs. Fuzzy's output is accepted as the input dataset for FL. In addition, four measurements—vehicle node density (ND), speed, vehicle node distance (NDS), and residual energy (RE)—have been presumptively taken into account when determining whether a node can execute the CH component or not. As the battery power is essentially irreplaceable and the vehicle has power limitations for processing and communication, RE is one of the sustainable factors for choosing CH. Data transmission would need more energy from nodes if this CH were much farther from the BS. As a result, the NDS is used as another consideration. Due to their distribution in the area, the automobiles near the CH illustrate the second node density condition. Accordingly, every vehicle has a unique number of neighbour nodes; when they select a vehicle as CH with a small number of nearby vehicles in their transmission range, these vehicles are unable to transmit directly to the CH and must instead use intermediary nodes, which raises the cost of transmission. As a result, ND was another factor taken into account. The fuzzy logic system has been presented in figure 3.

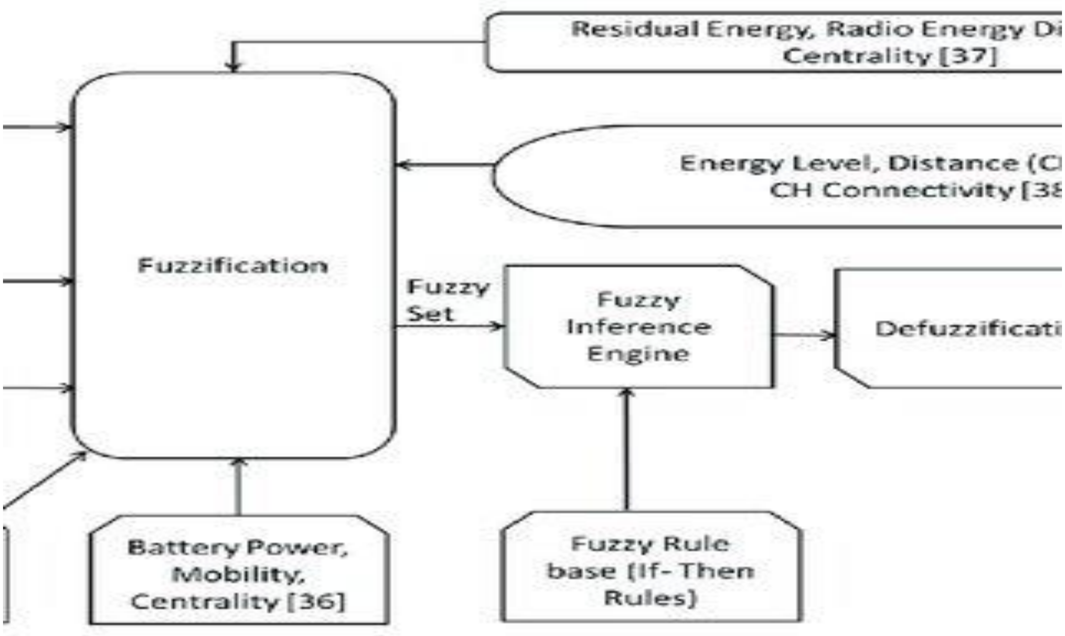


Fig.3: Structure of proposed Fuzzy logic system in VANETs

Three levels of fuzzy logic's primary operations are fuzzification, fuzzy inference, and defuzzification. In this section, numerical values are "fuzzified," or transformed into fuzzy values using a fuzzy member function (MF). Three inputs—ND, RE, and NDBS—lead to a single output—randomness (CH). The established 30 "if-then" rules of the offered FL method are based on the linguistic function.

Layer 1: Fuzzification

This section describes the main characteristics of a vehicle that is fundamentally appropriate based on backward pass (shown as a square adaptive vehicle) and resembles all input parameters in comparison to MF. The MF graph was created with flexible vehicles in mind, so any one may use it to describe its output.

$$L_1 = \alpha_{X\omega}(A) = \exp\left[-\left(\frac{m-f_\omega}{2d_\omega}\right)^2\right] \tag{1}$$

$$\alpha_{X\omega}(A) = \frac{1}{1+\left|\frac{m-f_\omega}{d}\right|^2 * e\omega} \tag{2}$$

Layer 2: Rules based Fuzzy inference engine

The sender node uses the IF/THEN criteria to determine the rank of the node in this layer, which takes into account the fuzzy values of distance factor, direction, and mobility factor. The following is a definition of the linguistic rank variables: (perfect, good, acceptable, not acceptable, bad, very bad).

$$L_2 = \begin{cases} R_{1,\omega} = \alpha_{X\omega}(A), \omega = 1,2,3 \\ R_{1,\omega} = \alpha_{Y\omega}(B), \omega = 1,2,3 \\ R_{1,\omega} = \alpha_{Z\omega}(C), \omega = 1,2,3 \end{cases} \tag{3}$$

Presumed that A is the source vehicle for ω and $\alpha_{ai}, \alpha_{bi}, \alpha_{ci}$ that the degrees of MF are those that correspond to the linguistic parameters A_i, B_i and C_i and $\{d_i, e_i, f_i\}$ that the variable set of MF/premise variables. In this stratum, it was allowed to input vehicles with trapezoidal and triangular MF forms.

3.2. DSOR based routing technique

The organisation of optimization There are three stages in DSOR, including periods for network simulation, traffic creation, and optimization. The suggested approach creates an optimization structure that the DSOR algorithm executes. For improved formation in continuous search space, the DSOR method is used. The artifact's focus on fitness function, which is used to give the fitness value to DSO setups, is a significant part of its functionality. The transmission cost (Fitness value) is shown in order to choose an acceptable route design. The proposal impact was defined as both a network expansion during the route discovery phase and a reduction in routing overhead. This method makes use of the shared capabilities of automobiles to provide various urban circumstances the exact status.

In Equation (5) demonstrates Ψ_{QQ} the DSOR algorithm's fitness function is generated

$$\Psi_{QQ} = w_1 * (Q_{PDR}) + w_2 * (Q_D) + w_3 * (Q_{NDP}) + w_4 * (Q_{NDL}) + w_5 * (Q_T) \quad (4)$$

Moreover, the formula includes weight factors w_1, w_2, w_3, w_4, w_5 whose definitions depend on the importance of each measure in the network.

People easily observe that doves forage at plazas where there are crumbs around and each dove searches crumbs. Some doves may be satisfied but not for all. One may observe that unsatisfied doves fly forward to spots for more crumbs. The optimization goal function used in this approach is $\Psi_{QQ}(W)$. Each data pattern, W is seen as a location with crumbs in a data collection, and the quantity of crumbs in these positions W , $\Psi_{QQ}(W)$ has crumbs. The location with the most crumbs is the greatest option.

Procedure for DSO algorithm

Step1: Determine the number of doves, then place them on the problem-solving area. Suppose that the quantity of doves is known in advance Q . the Network's nodes should be initialised. Where N specifies the number of nodes, $W_N = (1,2,..., N)$ the node value reflects the random value.

Step 2: Set the number of epochs $e = 0$ as well as the satiety level. the four neurons at the network's corners' weight vectors and edges.

Step 3: Use equation (5) to calculate the fitness function for all-doves.

$$OF = \Psi_{QQ} \quad (5)$$

Step 4: Find the dove e using the maximal criteria at epoch that is A_u^e closest to the most crumbs.

$$A_u^e = \mathrm{ArgMax}\left\{\Psi_{QQ}{}_u^e\right\}, \mathrm{for}\, u = 0,1,\ldots.N \quad (6)$$

Step 5: Calculate the updated satiety degree for each dove using the equation below:

$$\Omega_u^e = \beta\Omega_u^{e-1} + e^{\left(\left(\Psi_{FF_u}\right)-\left(\Psi_{FF}^{df}\right)\right)}, \; for \; u = 1,2,.......N \quad (7)$$

Step 6: The dove D_Ω^e with the greatest level of satiety should be chosen leveraging the maximum criteria and equation (8).

$$D_{\Omega}^{e} = Arg \underset{1 \le u \le N}{Max} \{\Omega_u^e\}, \quad for\ u = 1,2,\ldots, N$$

(8)

The dove D_{Ω} chosen by (8) is the one that exhibits the finest foraging behaviour and is deserving of imitation by the other doves in the flock.

Step7: Using the maximum criteria below to update the position vectors for each dove.

$$QQ = QQ_u^e + \lambda \delta_u^e \left(QQ_{D_\Omega}^e - QQ_u^e\right) \tag{9}$$

Where,

$$\delta_u^e = \left(\frac{\Omega_{bs}^e - \Omega_u^e}{\Omega_{bs}^e}\right)\left(1 - \frac{\left\|QQ_u^e - QQ_{D_\Omega}^e\right\|}{\text{MaxDis tan ce}}\right) \tag{10}$$

$$\text{MaxDis tan c e}: \underset{1 \le u \le N}{\text{Max}} \left\|QQ_u - QQ_v\right\|$$

(11)

The learning rate for δ updating the dove position vector is one of the parameters. The next step provides comprehensive explanations of modifying Equations (09) through (11).

Step8: Continue to step 3 and add one additional epoch $(i.e., e = e + 1)$ until the terminate condition is satisfied. Figure 4 depicts the suggested DSO algorithm's flowchart.

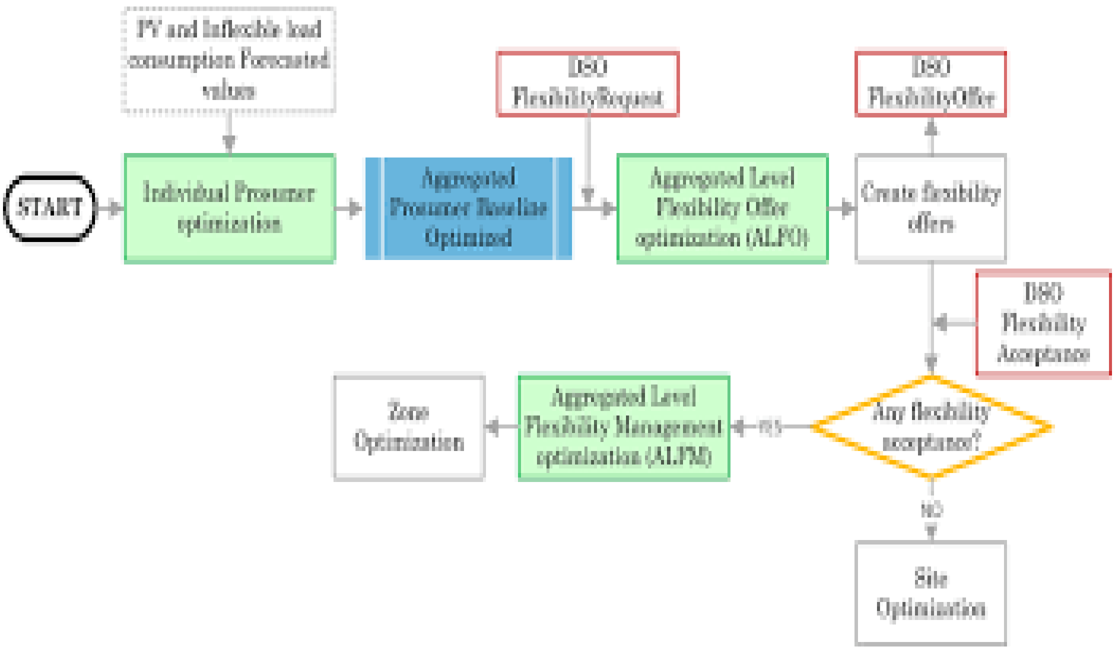


Fig.4: Flowchart of proposed DSO

4. Performance Evaluation

The proposed routing protocol was simulated using MATLAB simulation tools. Using MATLAB software (2022 b) and an Intel Core i7-2450M CPU 2.50GHz laptop with 8GB Memory, the proposed technique is used to authenticate the attendance of the predictable and routing protocol. The messages that include standard text content are taken into consideration in order to verify the performance of the suggested approach. Performance indicators like throughput, drop, overhead, and performance indicators like delay and delivery ratio may be used to examine the suggested method. The two bases of arrival rate-based results and time-based outcomes, respectively, are used to validate the proposed approach. Table 1 lists the implementation variables for the suggested approach.

Table 1: Simulation parameters

S. No	Description	Parameters
1	Radio Range	200m
2	Road Side unit	15
3	Short time period	10 seconds
4	Road length	10 km
5	Number of Access point	10
6	Channel model	Fading channel model
7	Signal to Noise ratio	30dB
8	Simulation Area	500m *500m
9	Road configuration	2 lane in each direction
10	Traffic constant	0.50
11	Packet Size	1 TB
12	Data generation	Poisson distribution
13	Vehicle speed	15-35 m/s
14	Number of vehicles	125
15	Mobility model	Random waypoint

4.1. Performance Metrics

The proposed protocols' performance was assessed and compared to existing protocols using the metrics delay, overhead, delivery ratio, drop, and throughput. This section explains each of these parameters and compares the RNN-DOA (Recurrent Neural Network Dragonfly Optimization Algorithm), Recurrent Neural Network-Particle Swarm Optimization (RNN-PSO),Recurrent Neural Network-COOT and proposed protocols.

4.1.1. Analysis of Packet delivery ratio (PDR)

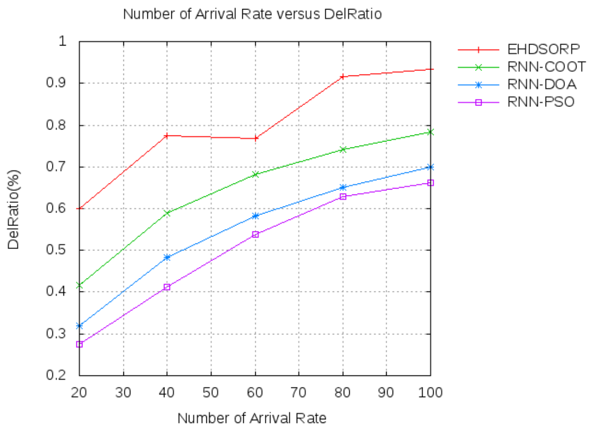
Packet delivery ratio measures the ratio of total packets successfully delivered to the destination to the total packets broadcast from the source node. For calculating the Packet delivery ration, equation (12).

$$PDR = \frac{Number\ of\ \ packets\, received\ by\ the\ destination}{Number\ of\ \ packets\, sent\ by\ the\ source}$$

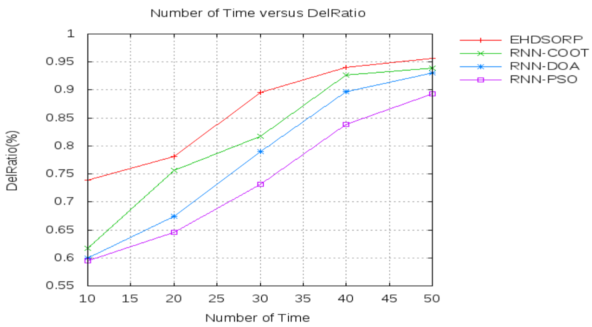
(12)

The success of the protocol in delivering data packets can be determined by packet delivery rates. The greater Packet delivery ratio indicates that the protocol has delivered packets more effectively.

The communication links between the vehicles are less likely to be broken when the number of arrival increases, resulting in fewer dropped packets and higher packet delivery rates. Figure 5(a) illustrates the breaking of the communication link between vehicles due to the high speed of the vehicles is regarded as one of the main concerns in intervehicle networks.The impact of increasing the number of times on the proposed protocol's packet delivery rate in various modes is shown in Figure 5(b). In the proposed protocol, 97% of vehicles are RSU. Moreover, the suggested protocol outperforms other known techniques as Recurrent Neural Network - COOT, RNN-DOA (Recurrent Neural Network Dragonfly Optimization Algorithm), and Recurrent Neural Network- Particle Swarm Optimization (RNN-PSO).



(a)



(b)

Fig.5: Performance analysis of increasing the number of vehicles on the percentage of packet delivery rate in (a) Arrival rate and (b) Time

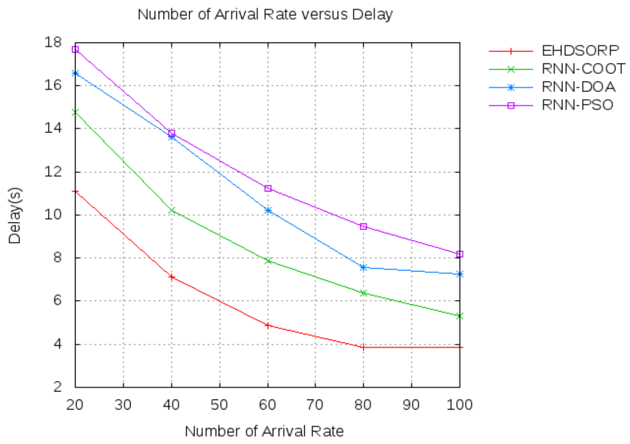
4.1.2. Analysis of delay

The average amount of time it takes to transfer a packet between two end nodes is the definition of the delay. Equation is used to compute this parameter (13).

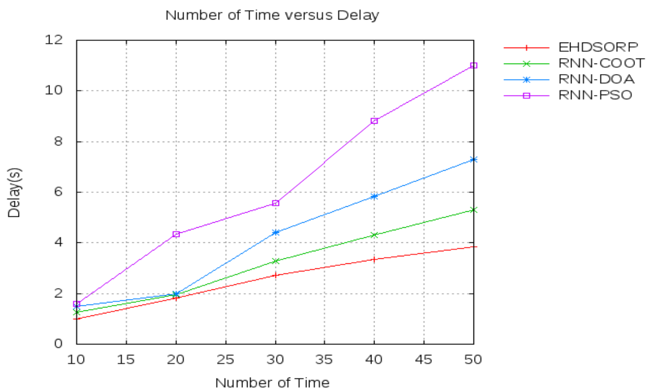
$$D = \frac{\sum_{x=0}^{q} \left((time\ \ of\ receiving\ the\ xth\ \ packet) - (time\ of\ \ sending\ the\ xth\ \ packet) \right)}{total\ number\ of\ \ packets\ received\ by\ the\ destination}$$

(13)

The average delay between the recommended method and the RNN-COOT, RNN-DOA (Recurrent Neural Network Dragonfly Optimization Algorithm), and Recurrent Neural Network- Particle Swarm Optimization (RNN-PSO) algorithms is shown in Figure 6. The number of routers between the source and destination causes the latency to decrease as the number of cars increases. Figure 6(a) demonstrates that under both normal and busy network conditions, the number of arrival rate based proposed protocol performed better than the three other protocols. The number of routing steps between the source and the destination are decreased by the proposed protocol for intervehicle networks' usage of RSUs, as was previously mentioned. The number of time-based packets sending steps between source and destination reduces as the number of RSUs in Figure 6(b) grows, resulting in a decreased end-to-end latency.



(a)



(b)

Fig.6: Performance analysis of delay in (a) Arrival rate and (b) Time

4.1.3. Analysis of Number of Dropped Packets

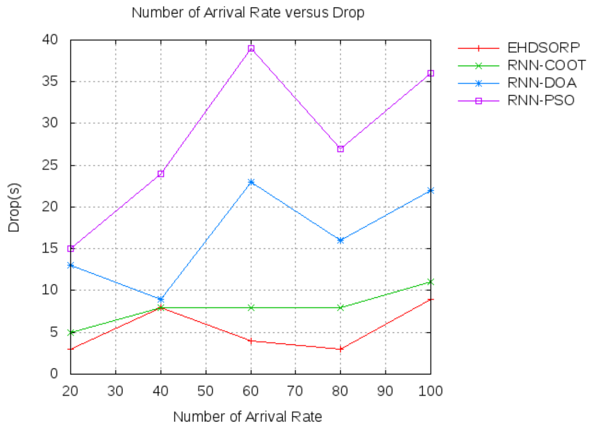
The proportion of packets that were lost throughout the simulation and did not make it to their destination is shown by this parameter. Equation can be used to determine the Number of Dropped Packets (14).

$$NDP = \frac{(Sent\ packet - received\ packet)}{100}$$

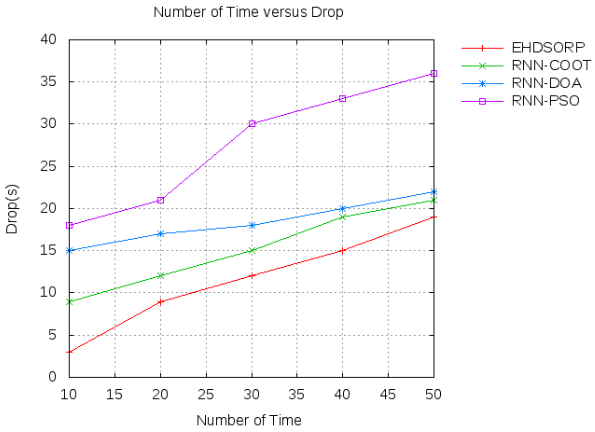
(14)

It becomes less common for linkages to break between vehicles as the number of vehicles increases. As a result, there are fewer lost packets.

It was suggested in the section on packet delivery rates that connections in intervehicle networks are less likely to be disrupted because of the high speed of moving vehicles. Hence, as the number of arrivals rises, the packet delivery rate also rises. As the number of dropped packets in the network and the packet delivery rate are inversely connected, the number of lost packets decreases as the packet delivery rate rises. The findings are shown in Figures 7(a) and (b). By increasing the number of arrivals and the duration, the network experiences a reduction in lost packets.



(a)



(b)

Fig.7: Performance analysis of dropped packet in (a) Arrival rate and (b) Time

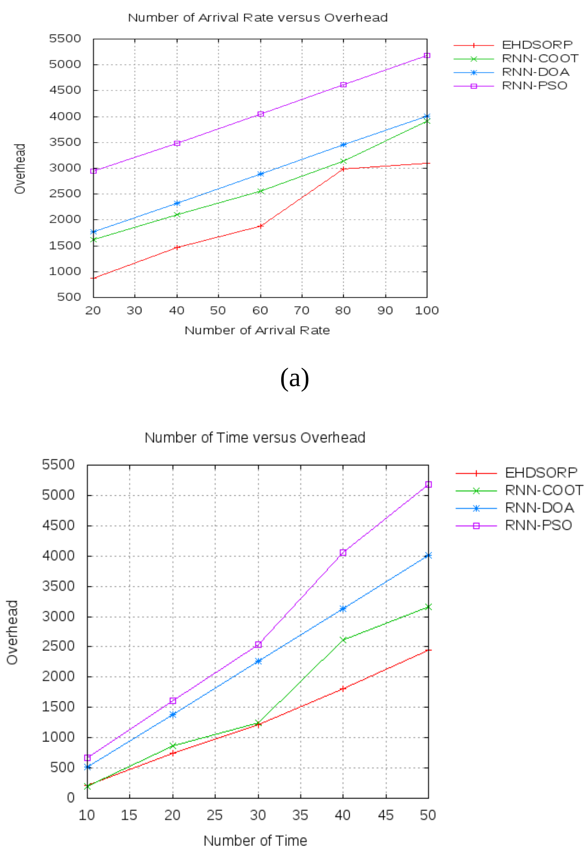
4.1.4. Analysis of Normalized Routing Load (NRL)

Equation can be applied to determine this parameter, which is defined as the proportion of routing packets transmitted to packets received (15).

$$NRL = \frac{Number\ of\ \ routing\ packetssentby\ the\ source}{Number\ of\ \ packets\ received\ by\ the\ destination}$$

(15)

The performance and efficiency of the procedure decrease as Normalized routing load increases.



(b)

Fig.8: Performance analysis of routing overhead in (a) Arrival rate and (b) Time

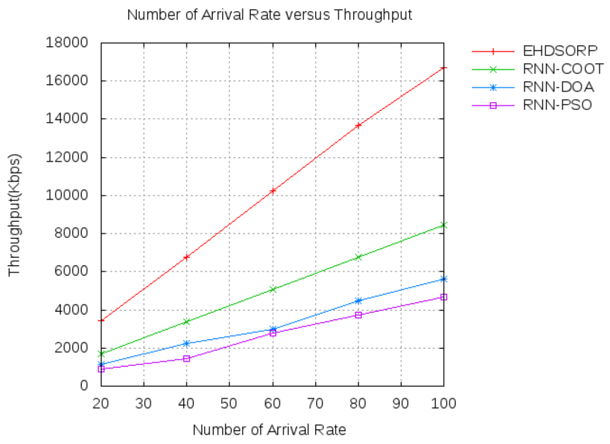
When there are more vehicles, more operations are being done on packets, which increases the routing overhead. Yet, as seen in Figure 8, the proposed protocol's routing expense is less than that of other current approaches like the RNN-COOT, RNN-DOA (Recurrent Neural Network Dragonfly Optimization Algorithm), and Recurrent Neural Network- Particle Swarm Optimization (RNN-PSO) algorithms. As shown in Figure 8(a), as the number of arrival rates rise, so does the number of arrival rates applied to routing packets. Yet, as shown in Figure 8(b), an increase in time causes a rise in the steps required to get there, which leads to fewer routing operations and ultimately reduced overhead.

4.1.5. Analysis of Throuput

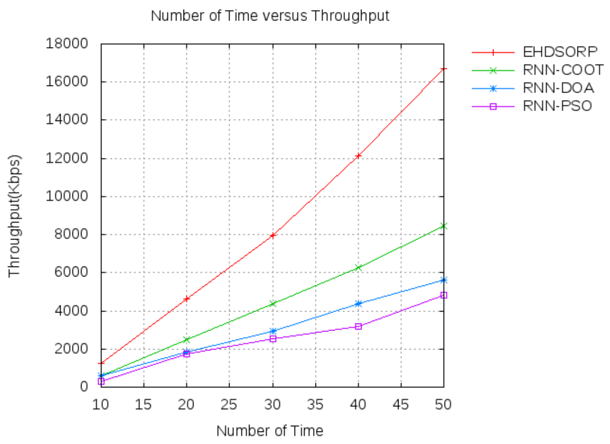
The percentage of all data bits delivered to the destination during the course of the simulation r is referred to as throughput. Typically, it is expressed in kilobits per second. The R is determined using equation (16).

$$R = \frac{\sum_{x=0}^{q}(\text{packetsreceived})}{r} \tag{16}$$

Using variables like the number of packets received at the destination and the length of the simulation (t), the throughput is estimated for each scenario. The total of the packets that were received and the time unit (t) are mathematical concepts leveraging in throughput calculations. According to equation, throughput is the proportion of total data bits received (16).



(i)



(ii)

Figure.9: Performance analysis of network throughput rate in (i) Arrival rate and (ii) Time

The network throughput rate findings are shown in Figure 9(i). The vertical axis displays the throughput rate in kilobits per second, while the horizontal axis displays the simulation duration in seconds. As additional routing channels may be found in the network by increasing the number of cars, the network's overall throughput will likewise rise. The performance study of time-based network throughput has been depicted in figure 9(ii). Since there are more nodes providing connection as the number of cars rises, the average throughput in this figure rises as the number of vehicles does, as predicted. As a result, the likelihood that packets will reach their destination improves, increasing average throughput. The findings show that SE-HFLDSOR outperforms existing approaches like RNN-COOT, RNN-DOA (Recurrent Neural Network Dragonfly Optimization Algorithm), and Recurrent Neural Network- Particle Swarm Optimization (RNN-PSO) in terms of throughput as it finds optimum routes.

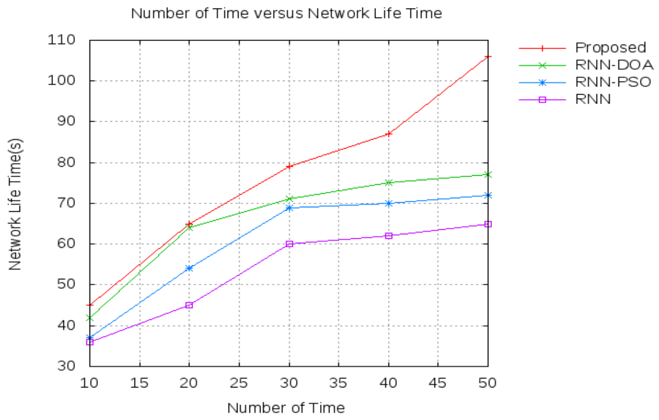


Figure.10: Comparative analysis of network lifetime

Fig. 10 displays the simulation results of end-to-end latency for SE-HFLDSOR and the three currently used routing strategies. In order to choose the shortest and routes with the maximum lifespan, SE-HFLDSOR takes into account the vehicle's movement, the link lifetime, and the distance to the destination node. This reduces packet delivery delay. From the above figure, it is clear that the suggested protocol has a longer lifespan than more established techniques like RNN-COOT, RNN-DOA (Recurrent Neural Network Dragonfly Optimization Algorithm), and Recurrent Neural Network- Particle Swarm Optimization (RNN-PSO).

5. Conclusion

Ever changing topology and ongoing network disconnections, which cause delays in package delivery, are the primary problems of VANETs. In this research, a novel balancing security-based energy-aware routing leveraging the SE-HFLDSOR protocol for VANET is created. In order to gather data about their immediate surroundings, the cars are first connected to the network and made to interact with one another. The FL approach is then used to choose CHs and build clusters by connecting adjacent nodes to CHs in the next step. Next, leveraging three input parameters, the FL technique is deployed to determine residual energy, distance, and node degree. Also, the optimal collection of inter-cluster communication channels is selected using the DSOR method. For assessing the suggested protocol's effectiveness and contrasting it with traditional approaches, the acquired results were examined in relation to certain characteristics including end-to-end latency, packet delivery percentage, and throughput. In order to demonstrate the effectiveness of the SE-HFLDSOR technique, the simulation results have been examined using a variety of parameters. The suggested SE-HFLDSOR protocol has the lowest transmission delay, highest throughput, and least amount of energy use. Steganography-based data aggregation solutions in the future have the potential to increase network performance and provide full balancing security. Hybrid deep learning models may be developed for VANET intrusion detection as well.

6. References

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