Performance evaluation of vertical handover in Internet of Vehicles

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Abstract

Internet of Vehicles (IoV) is developed by integrating the intelligent transportation system (ITS) and the Internet of Things (IoT). The goal of IoV is to allow vehicles to communicate with other vehicles, humans, pedestrians, roadside units, and other infrastructures. Two potential technologies of V2X communication are dedicated short-range communication (DSRC) and cellular network technologies. Each of these has its benefits and limitations. DSRC has low latency but it limits coverage area and lacks spectrum availability. Whereas 4G LTE offers high bandwidth, wider cell coverage range, but the drawback is its high transmission time intervals. 5G offers enormous benefits to the present wireless communication technology by providing higher data rates and very low latencies for transmissions but is prone to blockages because of its inability to penetrate through the objects. Hence, considering the above issues, single technology will not fully accommodate the V2X requirements which subsequently jeopardize the effectiveness of safety applications. Therefore, for efficient V2X communication, it is required to interwork with DSRC and cellular network technologies. One open research challenge that has gained the attention of the research community over the past few years is the appropriate selection of networks for handover in a heterogeneous IoV environment. Existing solutions have addressed the issues related to handover and network selection but they have failed to address the need for handover while selecting the network. Previous studies have only mentioned that the network is being selected directly for handover or it was connected to the available radio access. Due to this, the occurrence of handover had to take place frequently. Hence, in this research, the integration of DSRC, LTE, and mmWave 5G is incorporated with handover decision, network selection, and routing algorithms. The handover decision is to ensure whether there is a need for vertical handover by using a dynamic Q-learning algorithm. Then, the network selection is based on a fuzzy-convolution neural network that creates fuzzy rules from signal strength, distance, vehicle density, data type, and line of sight. V2V chain routing is proposed to select V2V pairs using a jellyfish optimization algorithm that takes into account the channel, vehicle characteristics, and transmission metrics. This system is developed in an OMNeT++ simulator and the performances are evaluated in terms of mean handover, handover failure, mean throughput, delay, and packet loss.

Keywords
4G LTE, DSRC, Internet of Vehicles, mmwave 5G, Network selection, Vertical handover.

The goal of IoV is to allow vehicles to communicate with other vehicles, humans, pedestrians, roadside units, and other infrastructures. Such communications are classified into five categories that are referred to as V2X communication (X: vehicles, RSU, infrastructure, humans, and pedestrians). The vehicles transfer both safety and non-safety data at different data rates. Safety data as an accident, road traffic, and others, while non-safety data such as video streaming, gaming, and so on. Integration of IoV with advanced wireless communication technologies such as 5G makes it a heterogeneous network (Ndashimye et al., 2020). It composes of Wi-Fi, Long-Term Evolution (LTE), and others. In general, vehicle communication is supported for both safety and non-safety data transmissions. The vehicles use dedicated short-range communication (DSRC) which enables low latency communication for short-distance vehicles.

In IoV, vehicles use DSRC for communication; however, due to its shorter range and bandwidth limitations, it is not suitable for long-distance communications and bandwidth greedy applications. Hence, IoV integrates with 5G to provide high data rates for communication. However, it suffers from blockage issues as it is unable to penetrate through obstacles (Choi et al., 2018). Besides, LTE also provides long-distance communication because of its coverage range, and high bandwidth features. Each radio access technology has its benefits and limitations.

Vehicles are equipped with multiple antenna terminals that enable to access different radio access network (RAN). Due to the use of different RAN in a network, a network introduces the process of vertical handover (VHO) (Sheng et al., 2018). 5G comprises different radio access technologies due to the presence of different cells such as microcell, femtocell, and nanocell. Each cell will be having more than one RAN and hence, requires selection of the best network (Jubara, 2020). Several multi-criteria decision-making algorithms have been proposed for network selection. In general, this type of algorithm takes into account multiple parameters and computes them for decision-making. The TOPSIS is one of the decision-making algorithms. This type of multi-criteria decision algorithms is popular in the selection of networks. IoV enables allowing data transmission of the highway and urban roadways in an autonomous vehicle (Storck and Duarte-Figueiredo, 2019). If there is an increase in the vehicle density, then the number of requests from the vehicles for vertical handover will also gradually increase.

The vehicle is built with more than one antenna terminal. The support of different RAN technologies requires selecting a network when one or more RAN is present in the coverage range.

The network selection process is also performed using optimization, reinforcement learning methods, and access network discovery and selection function (ANDSF) (Ndashimye et al., 2020). Q-learning is an algorithm that can decide concerning the environment. In IoV, vehicles move at very high speeds with change in topology and connectivity, the data transmission relies on routing (Ndashimye et al., 2020). Routing is the process of transferring data from source to destination through relay vehicles (Ndashimye et al., 2020). In routing, the vehicles in a route are preferred by taking into account the vehicle-based metrics like traffic, vehicle capacity, reliability, mobility, and others. As per the estimation of the metrics, a route or path is identified and packet forwarding is performed in that route. The process of routing is subjected to some challenges as topology changes, time consumption in route selection, and so on. The algorithms and methods are proposed to solve these challenging issues.

The goal of this paper is to minimize the number of unnecessary handovers when there is a need for high bandwidth while the data type changes. This research builds a learning-based method to decide whether there is a need for handover and then it selects a network for handover. In this way, we can reduce the number of unnecessary handovers. Then, V2V routing is established to minimize the number of re-transmissions. A poor selection of transmission routes causes route failure that leads to an increase in the number of re-transmissions. To solve this issue, an optimization algorithm is used. The two main contributions of our proposed work are to perform handover using network selection and data transmission via the best route.

The rest of this paper is organized as follows: the second section presents the previous research works and methods, the third section gives a particular problem description, and the fourth section discusses the proposed algorithms of handover, network selection, and routing. The fifth section discusses the simulation results, and the sixth section depicts the conclusion with future research directions.

Related work

Prior works on handover

Handover (HO) in the vehicular network is challenging to perform since the mobility of vehicles changes. Many research works have studied this issue and performed handover without any degradation in

network metrics. In the study of Chang et al. (2019), a cluster-based handoff, and dynamic edge-backup node (DEBCK) is proposed where the vehicles on the road lane were clustered, and the backup node provides handoff. Here, the cluster head performs the handoff and the backup mobile edge vehicle. The three main parameters that were taken into account for handoff are storage, communication, and energy. The main drawback of this work is poor handoff performance of backup mobile edge and cluster head, and failure to perform handoff whenever there is a need. In the study of Jubara (2020) a procedure for HO was proposed with the aim of minimization of delay in HO. A cross-layer protocol in an adaptive L4 HO procedure begins to estimate signal strength and if the quality of the signal was poor, then the link between user and base station disconnects. Then the Stream Control Transmission Protocol (SCTP) is assigned to the new IP and it is updated to the layers. However, the signal strength was not the only significant metric to make HO decisions. Due to the mobility of the vehicle and moving pattern on the road lane, HO of moving vehicles was proposed (Choi et al., 2018). According to the idea of this work, a group of users consists of a mail leader, sub-leader, and follower. The sub-leader was selected based on the maximum number of connections. In case if more than one vehicle has similar characteristics then, a sub-leader was selected at random. Initially, the vehicle computes reference signal received power (RSRP), reference signal received quality (RSRQ), link quality, and is reported for HO decision. A decision tree was built for HO decision-making using RSRP measurement. But the vehicles HO in a group requires frequent computation in the group, as well as measurement, and hence the computation will be higher in this work. The network layer-based L2 extension HO scheme was proposed (Naeem et al., 2019) and the architecture consists of an access router (AR), roadside unit (RSU), and vehicles. This work defines two HO schemes as inter-AR HO and intra-AR HO. The key goal of this scheme was to minimize latency and improve the packet delivery ratio. A fuzzy logic model and Elman Neural Network (ANN) was designed to decide along with the assurance of QoS (Naeem et al., 2019). For HO decisions, the parameters that are taken into account as cost, transmission range, velocity, load, and capacity. Even though this work performs better, the time for HO decision consumes time which increases the delay in the HO that may cause packet drop and degrades packet delivery ratio. The paper (Singh et al., 2020) concentrates on

handover as well as routing. A handoff protocol was proposed that computes link expiration time (LET) for detecting the connectivity between vehicles. The partner selection protocols enable a selection of optimal partner nodes (PN). Initially, the route was determined from GPS information and then the partner in the routes was selected from the vehicular LET using the traffic information. The vehicle with a high LET will be selected as the optimal PN in the route. In this work, only a single metric was taken into account for selecting a route between source and destination. However, if an opposite moving vehicle with high LET cannot be selected as PN and hence it requires considering other parameters too. In the study of Leu et al. (2019), and enhanced Access Network Discovery and Selection Function (ANDSF) was presented to perform a BS selection in the network. This algorithm combines with multilayer perceptron (MLP). The parameters were load, signal strength, throughput, and delay. The traditional workflow of the ANDSF is illustrated in Figure 1.

The ANDSF was equipped within the EPC which was started to be used in 3G and also on advanced radio access networks. This server was employed to discover information, manage policies, select policies, manage rules, and others. The user equipment can be a sensor, vehicle, or any other device that can access radio technology. The server first discovers the device and then performs a change in the connectivity. The procedure works by the developed set of rules and policies.

The vertical HO was performed using multi-criteria methods by taking into account the significant parameters such as QoS, delay, cost, and others (Hamurcu and Eren, 2020). Due to the consideration of multiple metrics for HO decision using enhanced Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) fuzzy logic (Embus et al., 2020). The working of this combination of algorithm works as per the following steps:

- Step 1: creates decision matrix using the parameters that were involved for HO decision. The computation was executed for each available network in the coverage area.
- Step 2: apply the Euclidean distance formula for determining the normalized decision matrix.
- Step 3: computation of weighted normalized decision matrix based on the function of the cross product.
- Step 4: estimate two ideal solutions as positive and negative from the cost metric. Hereby a set of benefit-based criteria were used for positive ideal solution prediction.
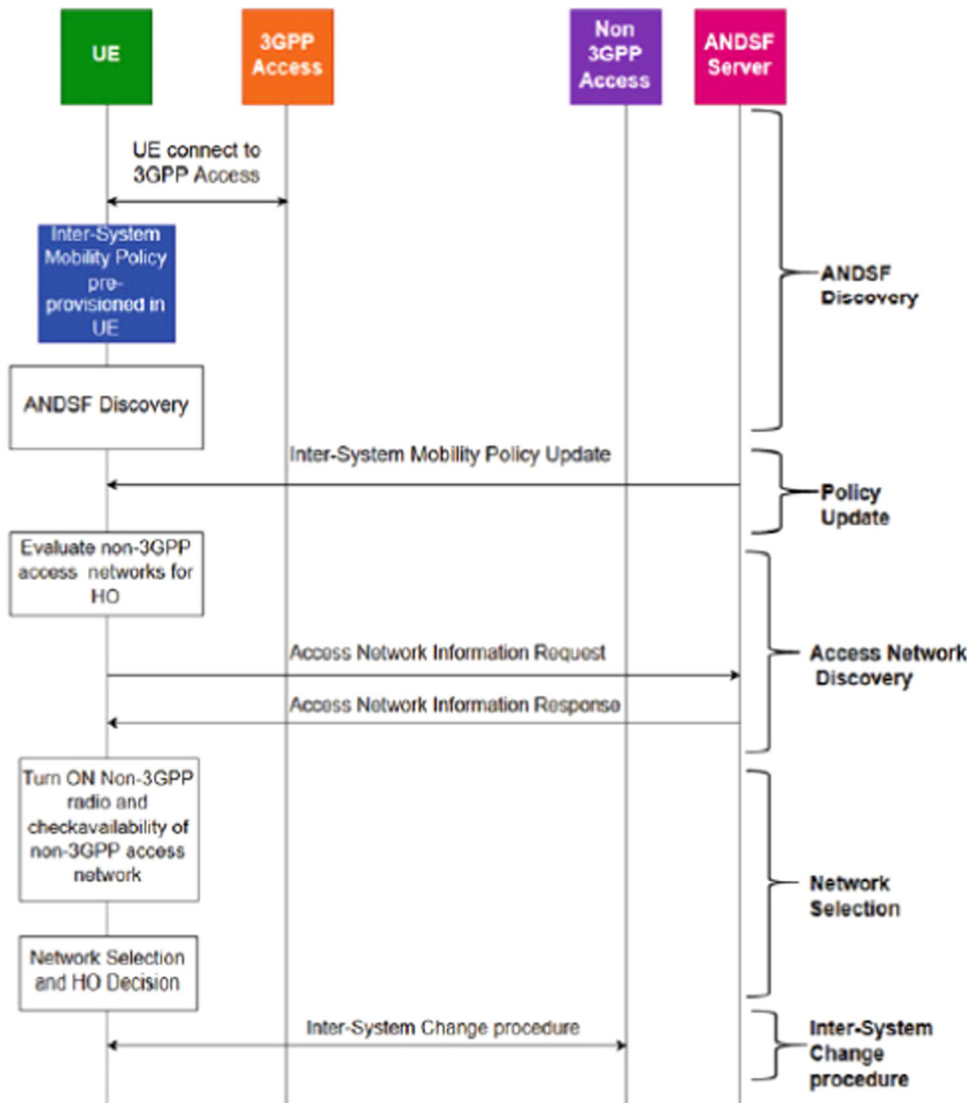
Figure 1: Workflow procedure of ANDSF (Ndashimye et al., 2020).

- Step 5: again use the Euclidean distance formula and determine the distance value for the estimated ideal solution.
- Step 6: compute relative closeness using the determined ideal solution in previous steps.
- Step 7: at the end, the ranking was performed from the determined closeness for each network, and based on this ranking, the best network was selected for HO.

The processing steps illustrated above for enhanced TOPSIS using fuzzy were able to overwhelm the problems in conventional RSS-based HO. Each step includes multiple criteria, these steps were not parallel, i.e. on each HO request, all the process requires to be performed and the decision was made after ranking.

Prior works on routing

The IoV environment that uses different types of radio access network due to the coverage range of each radio access. However, the vehicles have in-built DSRC for short-range data transmission, while the destination vehicle moves far from the source, then a route has to be preferred for data transmission.

Vehicles perform routing by selecting relay vehicles between the source and destination since the DSRC

range was small and hence it is not able to connect longer distance vehicles. In the study of Nguyen and Jung (2020), Ant Colony Optimization (ACO) algorithm is proposed with the idea of coloring vehicles. This algorithm presents two processes as solution construction and pheromone update. The idea of coloring was to give similar colors for the vehicles that have the same destination. As per the pheromone value, the route was selected in this work. However, this work failed to consider the significant parameters of the vehicles for the computation of the pheromone value that decides the transmission route. In the study of Al-Kharasani et al. (2020), a cluster-based adept cooperative algorithm (CACA) is proposed focusing on the QoS metrics. As per this work, clustering formation is done and a cluster head was selected. This work follows Optimized Link State Routing (OLSR) protocol with the Multi-Point Relay (MPR). This selection takes into account mobility factors, distance range, and quality of path (QoP). The vehicles that satisfy these parameters were selected as MPR and then the intersection vehicles were eliminated. The selection of MPR was not efficient, since the vehicles move at high speed. A protocol design was proposed, i.e. partner selection protocol that considers Vehicle Link Expiration Time (VLET) (Ndashimye et al., 2020). In this work the handoff means a vehicle disconnects from a partner node and joins a new partner node (PN), the partner node enables to perform data transmission. The only measure that was used in the selection of PN was not efficient since there are other significant metrics as signal strength which was also essential in node selection. A cross-layer design was proposed (Leu et al., 2019) that selects an optimal route based on the metrics forwarding probability, bandwidth, and link duration. The forwarding probability for the vehicle was formulated by considering velocity, distance, and communication range. The link duration was mathematically calculated as communication link lifetime that takes into account vehicle velocity, GPS location, and communication range. Then, the third parameter of bandwidth was calculated from link gain, noise power, and channel bandwidth.

The relay node selection was presented in the study of Cao et al. (2019) for relay selection using the estimation of curving rate. A double direction relay node selection was involved when the request to broadcast (RTB) was 1 and then it select relay from the estimation of curving rate, delivery ratio, one-hop delay, and message dissemination speed. The curving rate was formulated from the road length and the range of the vehicle. The computation of each parameter one after the other for route selection was time consuming and it leads to higher packet drop.

Routing is also performed using optimization algorithms. In the study of Leu et al. (2019), a hybrid optimization algorithm is proposed combining monarch butterfly and gray wolf optimization for route selection. The parameters that were taken into account for route selection are different costs computed for congestion, collision, travel, and QoS. For QoS prediction, fuzzy membership functions were applied. Initially, the butterfly algorithm was involved and then the gray wolf was performed for position updates and selecting optimal paths. The traditional issue in gray wolf optimization is its poor performance, and low accuracy. Fuzzy logic was also used to select routes by estimating link quality and achievable throughput. The link quality was based on the position, direction, and expected transmission count. As per the fuzzy weight, the output of the selection of next hop relay was performed. However, this work failed to tolerate the mobility issues concerning vehicular communication.

Problem definition

Issues concerning handover, network selection, and routing are discussed in this section from the previous research works. In the study of Ndashimye et al. (2020), the author proposed reinforcement learning algorithms. TOPSIS, K-Nearest Neighbor (K-NN), and AHP are proposed for handoff decisions considering bandwidth, network cost, preferences, connectivity probability, and signal to noise ratio (SNR) as the evaluation metrics.

- TOPSIS algorithm are subjected to rank reversal problem that either includes or eliminates the order of preferences. Besides this problem, it performs poorly to make vertical handover decisions.
- The handover is performed by the vehicle based on the ranking results the vehicle. However, the need for handover is not evaluated. Also, if all the vehicles requests for handover then TOPSIS had to perform the handover individually since the parameters differs for each vehicle.
- The use of k-NN for handover decisions was not efficient, since the k-NN algorithm gives higher accuracy in results only when the link quality was better. Also while the arrival of data was in large amount then the algorithm slows down to process and hence it takes time to make handover decisions.
- The data forwarding through these two metrics is not sufficient, since there may be a blockage that causes NLOS issues. This issue was common in mmWave and hence vehicle parameters

are essential to be considered while making for-warding decisions.

- The use of AHP was not efficient since it requires training of the data and then it can select the best path. But here as per the current situation of the vehicles the path needs to be selected and also the movement of vehicles will not be the same in all the regions. Also, the addition of new criteria was difficult in this algorithm.

Several algorithms have been proposed for the process of routing. Dijkstra algorithm and random relay selection are proposed for routing and data forwarding (Cao et al., 2019). QoS parameters are computed and estimated for the selection of routes. Since the movement of vehicles is dynamic and so, the management of the topologies is achieved by constructing the graphs.

The major problems identified in routing are as follows:

- The graph parameters are completely based on the past transmission history of the vehicles and the transmission of the vehicles depends on the channel metrics. Using these metrics, the graph was not able to predict the signal strengths with its neighboring vehicle. Consequently causing frequent handover.
- The maintenance of graphs is complex due to mobility concerns, hence it needs large resource blocks and dynamic processing to manage the graph.
- The random selection of radio networks with individual parameters may leads to poor performance of networks since the main constraints of QoS in this work is bandwidth or delay, i.e. it considers anyone from this, and hence the network selection is poor.

All of the above-highlighted gaps concerning handover, network selection, and routing are addressed in our proposed work.

Proposed system

This section is broken down into four sub-sections to describe the environment and expand each algorithm concerning handover, network selection, and routing in this proposed research work.

System model

The proposed heterogeneous IoV network is designed with vehicles consisting of a 5G base station, LTE base station, RoadSide Unit (RSU), and vehicles. The entities that participates in this system are defined below.

Definition 1: Vehicle – the vehicle moves on a restricted path, i.e. on-road lane in which the path is pre-defined in a map. The moving speed of the vehicle depends on the vehicle. Vehicles have in-build GPS, using which their latitude and longitude information is gathered. The location of the vehicle and the speed of the vehicle is dynamic. Vehicles use DSRC and other advance Ran for data transmission. It transmits safety and non-safety data.

Definition 2: RSU – RSU is employed in IoV for performing communication with the infrastructure. This entity is static in the environment and also it enables DSRC for vehicles.

Definition 3: 5G mmWave base station (BS) – the BS is static and this allows to perform high speed–short-range communication. It can solve the lack of spectrum issue.

Definition 4: LTE BS – this BS is also static and it allows long-distance communication with higher bandwidth and comparatively high spectrum efficiency.

The proposed system model is depicted in Figure 2, which composes all the above-defined entities into the system. The road lane has 'n' number of moving vehicles in their direction on the road. In this work, the handover is a decision that will be taken by the vehicle only when the current base station link is not good. But in case of sudden need in transmitting a safety application, it makes network selection process at that moments along with the consideration of data type as one of the parameters. Handover decision is the decision by which the need for handover is determined and it performs handover to the available network. For handover decision dynamic Q-learning in which the threshold is set as per the environment. If the handover has to be performed, it then selects a network from fuzzy-convolution neural network (F-CNN). For network selection, the fuzzy rules are defined and used in CNN. Then routing takes place by using an optimization algorithm called jellyfish algorithm that selects V2V pairs between source to destination and so, it is called V2V chain routing.

Handover decision

Handover decision by dynamic Q-learning, the dynamic means to use threshold concerning the available network. Dynamic Q-learning algorithm determines the need for handover by evaluating vehicle speed and signal strength. We set the threshold for signal strength using Shannon entropy rule as shown in the following equation:

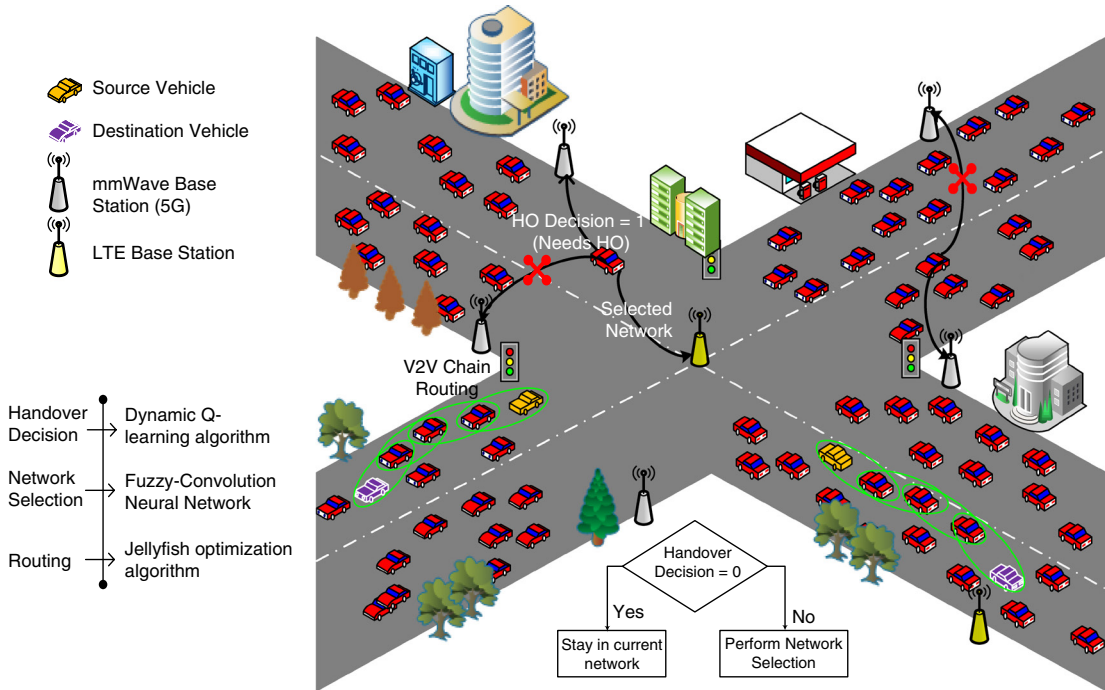$$S(ss) = E\left[-\log(P(ss))\right] \tag{1}$$

Figure 2: Proposed system model.

where $S(ss)$ denotes the Shannon entropy for signal strength that composes of ss values for DSRC, mmWave, and LTE that range between (-30 to -70 dBm). $P(ss)$ denotes the probability of the signal strength (Figure 3).

Let $Q(S,A)$ represent state S and action A based on the Q-values. Each state S will have two parameters and this $Q(S,A)$ is determined and updated in the rule. The temporal difference update rule is as follows:
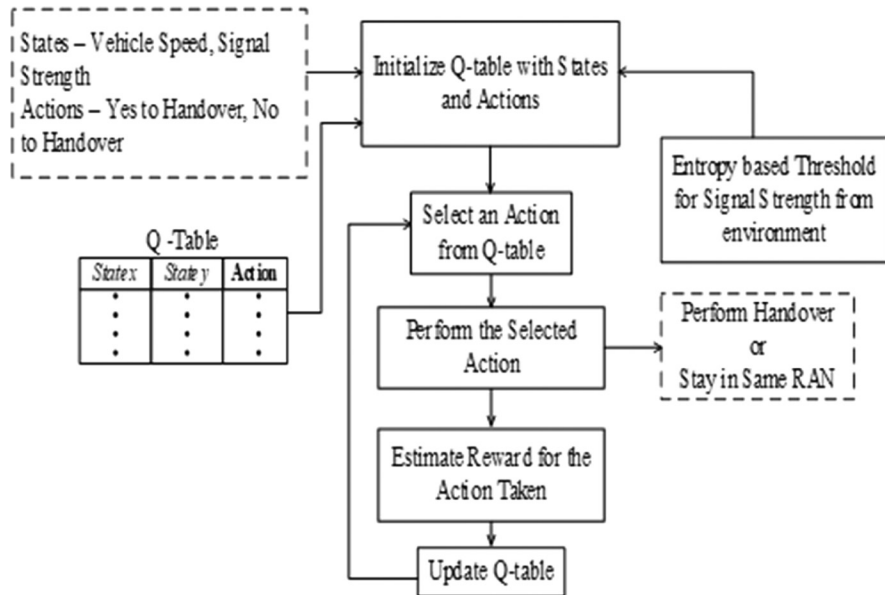

Figure 3: Workflow of dynamic Q-learning.

$$Q(S,A) + \alpha\left(R + \gamma Q\left(S^{'},A^{'}\right) - Q(S,A)\right) \rightarrow Q(S,A) \quad (2)$$

The term $Q(S',A')$ defines next state and action R is the reward given by the agent, γ is the discount factor that is [0–1], then α is the learning rate [0–1], i.e. it denotes the step length to estimate the (S,A). The action is taken using ϵ-greedy policy where ϵ represents epsilon. The pseudo-code for dynamic Q-learning is given below to decide the decision for handover:

Pseudo Code 1: Dynamic Q-Learning

Input – States (S), Q − $table$

Output – Action (A)

1. begin

2. $V_1(Req) \rightarrow HO$ //Vehicle 1 requests for handover

3. initialize Q-table

4. initialize $Q(S,A)$

5. for each $S \rightarrow ss, speed$ // Vehicle 1 parameter

6. compute ss threshold using equ (1)

7. for (each step)

    apply ϵ −greedy policy

    obtain Q-value from Q-table

    perform action $A \rightarrow V_1$ // Action taken by vehicle 1

Network selection

Network selection is the process of selecting a network from the available RANs. F-CNN algorithm is applied for network selection. The CNN is designed with layers of convolution, max-pooling, and fully connected layers. The layers are employed with fuzzy rules that are defined from the metrics signal strength, the distance between BS and vehicle, vehicle density in serving BS, data type (safety or non-safety), and line of sight. The definition for each metric is depicted below.

Definition 1: Signal strength – signal strength defines the SNR which gives the number of signals. A channel will compose noise as well as signal, the high the noise, the channel is unfit for transmission. The SNR (S_r) is determined from signal power P_s, and noise P_N respectively. The formulation is:

$$S_r = \frac{P_s}{P_N} \quad (3)$$

Definition 2: Distance between BS and vehicle – the distance between BS and a vehicle is estimated using Euclidean distance. This measure defines the stability of the link, as the distance increases the link will be unstable and when the distance decreases the link will be stronger. Euclidean distance is computed using the following equation:

$$D_{(L_{BS},L_V)} = \sqrt{(x - x_1)^2 + (y - y_1)^2} \quad (4)$$

For computing distance, the coordinate points of the BS and vehicle is used. Distance $D_{(L_{BS},L_V)}$ is determined from the BS location coordinates of (x,y), and vehicle location coordinates of (x_1,y_1), respectively. The location of BS is fixed and so it requires to know only the vehicle coordinate for distance estimation.

Definition 3: Vehicle density – the density of vehicle V_D denotes the number of vehicles that are connected with that particular BS.

$$V_D = \sum (N_{CL}, N_{NL}) \quad (5)$$

where N_{CL} and N_{NL} represents the number of connected links and number of new links.

Definition 4: Data type – the data type in vehicles are two, they are safety and non-safety. In this work, safety is denoted as 0 and non-safety as 1. The safety messages will be of traffic information, high-speed vehicle information. This type of data has a higher priority in transmission than the non-safety data.

Definition 5: LoS – line of sight defines the direct contact between the vehicle and BS without any obstacles that block the signals. For transmission, LoS is only preferred and the signals in Non-LoS are not preferred.

The above five metrics involve the development of fuzzy rules. The fuzzy logic deals with the decision-making by the defined rules as shown in Table 1. The mmWave signals will be chosen for any type of traffic, but only when the LoS is present since blockage of mmWave leads to poor performance, in case of blockage the vehicle selection will be 4G LTE.

The fuzzy logic method operates with the IF-THEN rules in the interference engine. The input is in crisp values that are converted into a fuzzy set. As per the fuzzy rule, the interference engine constructs membership function between [0,1]. The fuzzy logic operations are built into CNN. Figure 4 depicts the constructed fuzzy logic with CNN. The output high (H), medium (M), and low (L) denotes as follows:

$$(H,M,L) \rightarrow (mmWave, LTE, DSRC)$$

Table 1. Fuzzy rules.

| Rule number	S_r	Distance	V_D	Data type	LoS	Output
			Input			
R1	H	H	H	H	H	H
R2	H	H	H	H	L	H
R3	H	H	H	L	H	M
R4	H	H	H	L	L	M
R5	H	H	L	H	H	H
R6	H	H	L	H	L	M
R7	H	H	L	L	H	L
R8	H	H	L	L	L	M
R9	H	L	H	H	H	H
R10	H	L	H	H	L	L
R11	H	L	H	L	H	L
R12	H	L	H	L	L	L
R13	H	L	L	H	H	H
R14	H	L	L	H	L	M
R15	H	L	L	L	H	L
R16	H	L	L	L	L	M
R17	L	H	H	H	H	H
R18	L	H	H	H	L	L
R19	L	H	H	L	H	H
R20	L	H	H	L	L	M
R21	L	H	L	H	H	H
R22	L	H	L	H	L	H
R23	L	H	L	L	H	L
R24	L	H	L	L	L	L
R25	L	L	H	H	H	H
R26	L	L	H	H	L	M
R27	L	L	H	L	H	L
R28	L	L	H	L	L	L
R29	L	L	L	H	H	M
R30	L	L	L	H	L	M
R31	L	L	L	L	H	L
R32	L	L	L	L	L	L
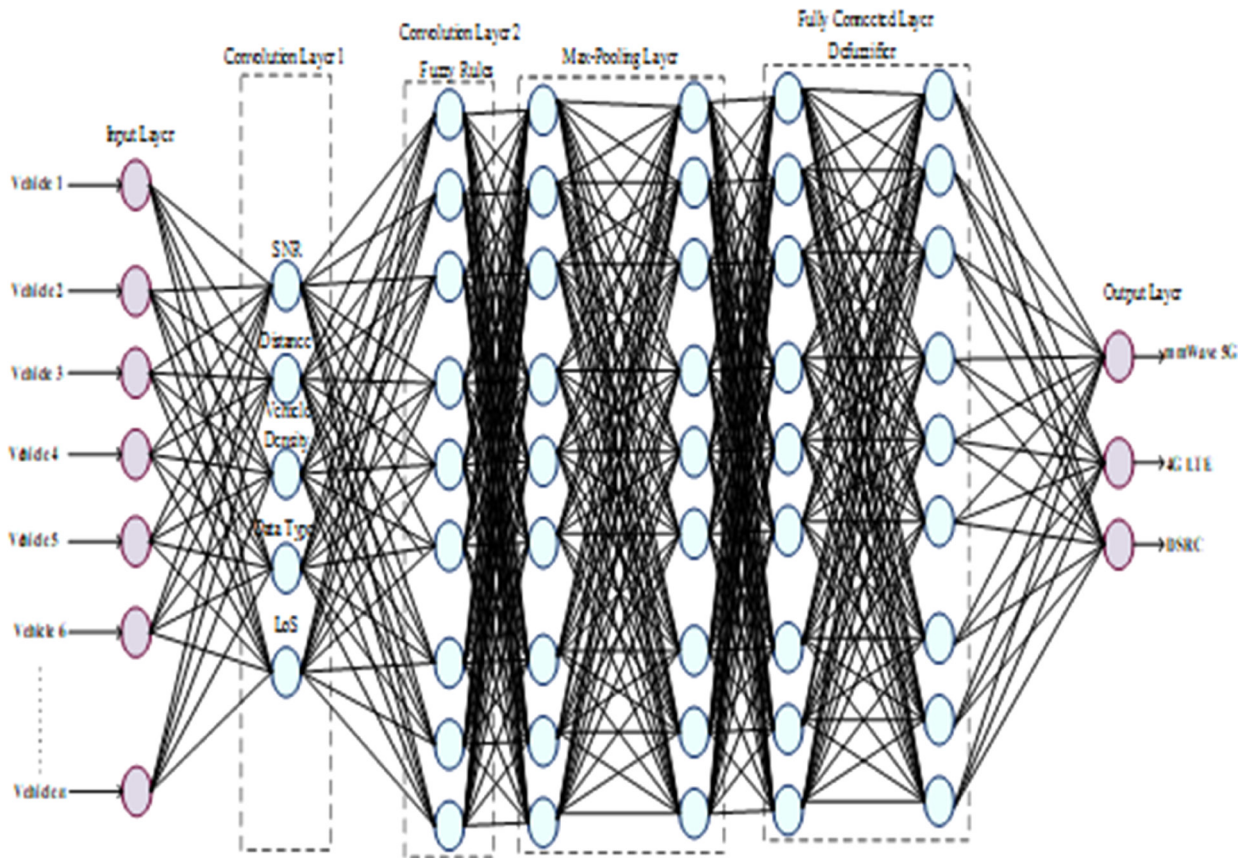
Figure 4: Fuzzy-convolutional neural network.

A pseudo-code below is illustrated based on the workflow of this fuzzy-CNN algorithm:

```
Pseudo Code 1: Fuzzy-CNN
Input – Vehicle Req
Output – Network Selection (N_S)
1. begin
2. V(Req) → N_S          //vehicle requests for
selecting network
3. for each (V → SNR, D, Density, DT, LoS) //
convolution layer 1
4. compute SNR, D using equ (3) and equ (4)
5. determine the density, LoS with target
network
6. for (each V) do
    apply Fuzzy Rule     // convolution layer
2
7. if (V = R1)
    {
    select network (H) or (M) or (L)
    else
    go to next rule
    }
    end if
```

```
8. repeat step 7 until rule is satisfied
9. sum-up fuzzy values for each V //max-
pooling layer
9. fuzzy set → crisp output   // fully connected
layer
10. return N_S               // output layer
11. end
```

The use of CNN will give results for multiple vehicles at the same time by parallel processing. The proposed fuzzy-CNN is composed of 32 rules, which are defined from five parameters. Since the CNN can process in parallel, the 32 rules will be processed in the convolution layer. According to the selected network, the requested vehicle will handover from the current network to the target network.

Optimized routing using jelly fish optimization algorithm

The process of routing is carried out using jellyfish optimization algorithm where the vehicles are formed

like V2V pairs, hence the name V2V chain routing. The routes are selected by computing the objective function using channel metrics (SNR (s_r), link quality (l_q)), vehicle metrics (Speed (s_p), Relative direction (R_d)), and vehicle performance metrics (Delay (D_l), throughput (T_p)).

A time control mechanism is used to switch between active or passive movements in this algorithm. The time control $c(t)$ is formulated and computed using the following equations:

$$c(t) = \left| \left(1 - \frac{t}{Max_{ite}} \right) \times (2 * rand(0,1) - 1) \right| \qquad (6)$$

when $rand(0,1) > (1 - c(t))$, then passive motion:

$$rand(0,1) < (1 - c(t)) \text{ then active motion} \qquad (7)$$

Here the jellyfish are assumed as vehicles and the ocean is assumed as road lane where the vehicle moves in different speed.

The ocean current direction represented as $\overrightarrow{OC}$ and it is mathematically given as below:

Let:

$$\overrightarrow{OC} = \frac{1}{V_p} = X^* - e_c \mu \qquad (8)$$

Then:

$$\overrightarrow{OC} = X^* - d_{ff} \qquad (9)$$

where 'V_p' is the vehicle density. X denotes the best location, μ is the mean location, and e_c is the attraction factor, here the attraction of on destination. Then, the objective function is defined to select a best route. This function OF is formulated as follows:

$$OF(Ms) = \sum (s_r, l_q)(s_p, R_d)(D_l, T_p) \qquad (10)$$

Ms represents a set of parameters in which the delay and speed must be minimum and all the other parameters can be a maximum value for the selection of the routes. Here the OF is applied for the complete route, since this work selects an optimal route from the available routes. The metrics are estimated from the channel:

$$l_q = \frac{1}{P_f \times P_r} \qquad (11)$$

$$R_d = 2r \sin \sqrt{\sin^2\left(\frac{\Delta_{la}}{2}\right) + \cos(la_v) * \cos(la_{np_i}) * \sin^2\left(\frac{\Delta_{ln}}{2}\right)} \qquad (12)$$

$$D_l = \frac{P_L}{b} \qquad (13)$$

where P_f, P_r represents the number of transmitted and the received packets in the same link between two vehicles, (la, ln) represents the latitude and longitude, (la_v, ln_v) represents the vehicle location, and (la_{np}, ln_{np}) represents the next hop location and r is the radius. P_L, b represents packet length and bit rate, i.e. transmission speed in bits per second that are used to compute the delay estimation.

Equation 10 defines the objective function through which the optimal route is selected using jellyfish optimization algorithm.

The performance of the proposed HO, network selection, and routing algorithms are evaluated in the next section.

Simulation results

The section is split into three parts as simulation setup and specifications, comparative analysis, and result discussion. The simulation details and the parameters are discussed in detail in this section.

Simulation setup and specifications

The proposed work is simulated using OMNeT++. Table 2 shows the simulation parameters assumed in our proposed work.

Table 2. Simulation specifications.

Parameter	Range/Value
Simulation area	2,500 m × 2,500 m
Number of vehicles	100
Number of 5G mmWave BSs	2
Number of 4G LTE BSs	2
Vehicle mobility type	Linear mobility
Vehicle speed	10-40 m/s
Transmission range	
DSRC	300 m (Max)
mmWave	~500 m
LTE	100 km (Max)
Transmission rate	3-5 packets per second
Packet size	512 bytes
Simulation time	1,000 sec

Comparative results

The comparative analysis gives the obtained results in comparative graphs. The proposed work is compared with previous works that use conventional RSS-based selection, TOPSIS, ANDSF, and V2I-MoloHA methods relating to handover, network selection, and routing issues. It is a multi-criteria decision-making algorithm that processes with more than one criterion. The parameters that are considered for the evaluation are mean handover, handover failure, throughput, and delay.

Mean handover and handover failure

The mean handover is the number of successful handovers of a vehicle from one network to another. Handover failure is defined as the number of unsuccessful handovers that happen due to poor decision-making.

The lesser mean handover denotes the better performance of the proposed algorithm as it has minimized the number of unnecessary handovers in the network. In previous work of TOPSIS, it was used for the selection of network that fails to perform proper ranking. Similarly, the use of parameters for the selection of network was either based on vehicle characteristic or environmental characteristic which leads to select the best target network that eventually increases mean handover along with the increase in the handover failure.

The proposed dynamic Q-learning algorithm can learn the vehicle environment in a particular surrounding. The prediction of handover requirement from the vehicle speed and signal strength is efficient. Further to the prediction, we perform a selection of networks using the F-CNN algorithm for selecting a network by analyzing the metrics of the particular vehicle. The process of prediction and network selection in this work tends to improve the performance of the handover-based metrics.

Figures 5 and 6 illustrate the mean handover and handover failure concerning the increase in vehicle speed. The improvement in the performances of HO failure rate and mean handover is due to the handover decisions made by dynamic Q-learning algorithm and appropriate selection of networks due to fuzzy-CNN. The mean handover in the proposed work decreases with the increase in vehicle speed and hence, suitable for large-scale environments. Besides, the decrease in mean handover reduces the HO failure counts. In general with the increase in vehicle speed, the handover failure occurs but as the proposed work uses Q-learning for predicting the requirement of
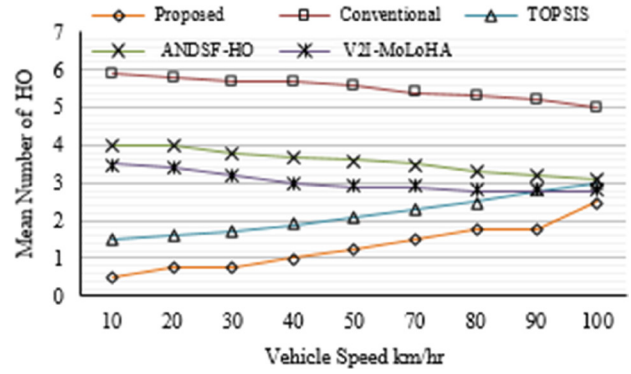

Figure 5: Comparison of mean handover (Ndashimye et al., 2020; Sheng et al., 2018).
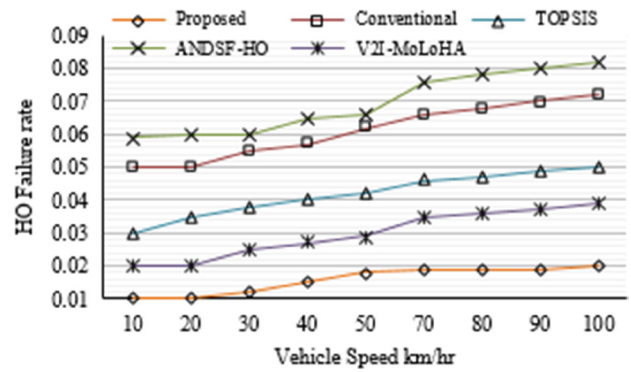

Figure 6: Comparison of HO failure (Ndashimye et al., 2020; Sheng et al., 2018).

handover before that of the network selection it can take an absolute decision at the increase of vehicle speed. The main reasons behind the degradation of handover are illustrated below.

Selection of parameters to select the suitable network which requires considering vehicle metrics as well as the BS metrics:

- The number of handovers increases due to the absence of prediction of the vehicle regarding the need for handover. This leads to an increase the number of unnecessary handovers which also requires large resource blocks for performing the computations.

The handover failure rate HO_{FR} is computed mathematically based on the below equation:

$$HO_{FR} = \frac{HO_F}{HO_S + HO_F} \qquad (14)$$

The terms HO_F and HO_S represents the number of handover failure and handover success, respectively. According to the count of these measurements, the handover failure rate is determined. The handover failure is caused because of the poor handover decision; hereby the proposed work first predicts the handover requirement from the vehicle request by learning the environment and then if the decision is to perform handover, it selects a target network. From the comparative graph, the average value of failure rate in proposed is 0.015, while the previous work achieves 0.13, 0.04, 0.07, and 0.03 in conventional, TOPSIS, ANDSF-HO, and V2I-MoLoHA, respectively. The minimization of handover failure reflects on absolute handover decision. Similarly, the reduction in the number of handover shows that the unnecessary handover is reduced by efficient prediction and network selection in proposed.

Table 3 gives a comparison on the average values estimated from the performance of conventional method, TOPSIS, ANDSF-HO, and V2I-MoLoHA in terms of number of handover and handover failure. Then the improvement percentage of handover efficiency is depicted in the above table. The handover efficiency impact on other network parameters that enhances overall network efficiency.

Throughput, delay and packet loss

Throughput is one of the significant performances metric in a network and it is mathematically computed using the formula as follows:

$$T = \frac{P_{sz}}{R_{tt}} \times \frac{1.2}{PL^{0.5}} \qquad (15)$$

The throughput T is estimated from the packet size P_{sz}, round trip time R_{tt} and packet loss PL.

Figures 7 and 8 show the graphs for throughput, and delay. From Figures 7 and 8, there is an increase in the throughput and decrease in delay when compared to the existing techniques. This is due to the optimal selection of routes using jellyfish optimization algorithm. The graph shows little increase, and drops in the delay. The end-to-end
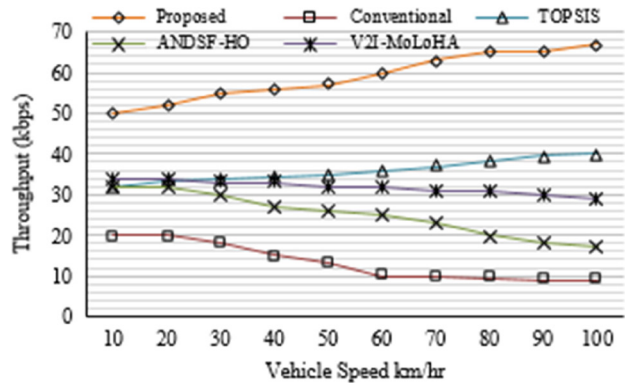

Figure 7: Comparison of throughput (Ndashimye et al., 2020; Sheng et al., 2018).
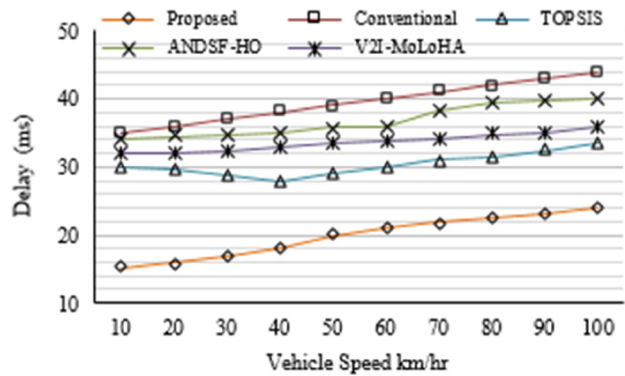
Figure 8: Comparison of end-to-end delay (Ndashimye et al., 2020; Sheng et al., 2018).

Table 3. Comparison of HO efficiency.

Method	Average number of HO	Better efficiency	Average HO$_{FR}$	Better efficiency
Conventional	5.51	55%	0.133	90%
TOPSIS	2.15	20%	0.041	40%
ANDSF-HO	3.57	30%	0.069	60%
V2I-MoLoHA	3.03	25%	0.029	20%
Proposed	1.30	–	0.01	–

delay is determined in terms of transmission delay between the relay vehicles from the source vehicle to the destination vehicle. The end-to-end delay (EE_D) is determined as follows:

$$EE_D = \frac{Nb(N_0,N_1)}{R(N_0,N_1)} + \frac{Nb(N_1,N_2)}{R(N_1,N_2)} + \cdots\ldots + \frac{Nb(N_n,N_m)}{R(N_n,N_m)}$$

(16)

Let the vehicles in a route be represented as N_0, N_1, N_2…,N_n, N_m for which the number of bits in each node is denoted as Nb and the rate of transmission is R. The N_0 is the source vehicle node, N_m is the destination vehicle node, while the nodes are the relay. In accordance to the estimation of the delay a better efficiency in the route selection is analyzed. In a route, the delay occur between every pair of vehicle due to the use of signal strength and hence the delay is predicted for each pair and end-to-end delay from the source to destination is determined.

The comparative results depict that proposed work is better than the previous conventional method, TOPSIS, ANDSF-HO, and V2I-MoLoHA. Among all the previous work, the conventional method of using only signal strength results in poor performance due to the growth of multiple challenges in data transmission of vehicles. Table 4 illustrates the mean value determined for each work in the performance of throughput and delay. Based on the mean throughput and delay, the percentage of improvement is proposed than the existing works. As per the comparison, a minimum of 23% and a maximum of 46% is better performance than the previous methods in this network (Table 5).

One of the major reasons for the increase in packet losses is due to the link degradation problems which occur mainly due to high vehicle density, poor signal quality. In our work, we have proposed a jellyfish optimization algorithm for the

Table 5. Comparison of packet loss.

Method	Packet loss (%)	Better efficiency
Conventional	48	21%
TOPSIS	32.4	12%
ANDSF-HO	24	19%
V2I-MoLoHA	18.8	16%
Proposed	12	–

selection of routes taking into account vehicle metrics, channel metrics, and transmission metrics. Figure 9 shows the graphical plots where there is a decrease in the packet loss concerning the vehicle density due to consideration of multiple metrics for selecting the shortest path. From the figure, when there is an increase in the vehicle density, there are possibilities of an increase in data transmission due to which the packet loss can increase. However, in our work, the packet losses are minimized due to the selection of optimized routes. The previous works of TOPSIS, ANDSF-HO, and V2I-MoLoHA fails to select the best route among the available route between source and destination. Therefore, the deployment of an algorithm for selecting the best route minimizes packet loss. Even the vehicle density increases there is a reduction in packet loss since not all vehicles will use the route for transmission. That is to say, the vehicles nearby will not require data transmission. Due to this reason, the packet loss in the proposed work does not increase suddenly with the increase in the number of vehicles.

Table 4. Comparison of throughput and delay.

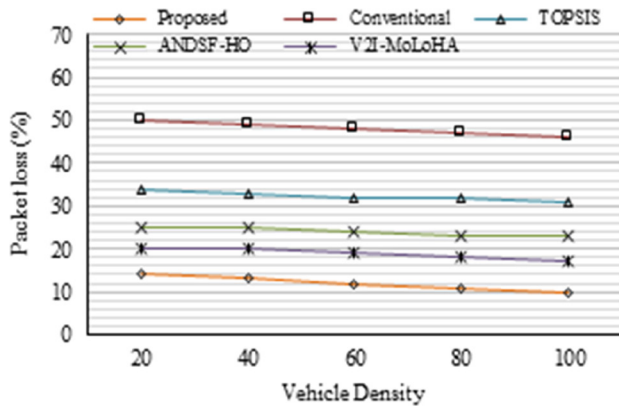| Method	Mean (kbps)	Better efficiency	Average delay (ms)	Better efficiency
Conventional	13.7	46%	39	21%
TOPSIS	35.96	23%	30	12%
ANDSF-HO	25	34%	37	19%
V2I-MoLoHA	31.89	27%	34	16%
Proposed	58.89	–	18	–

Figure 9: Comparison on packet loss (Ndashimye et al., 2020; Sheng et al., 2018).

Result discussion

In this section, the obtained results are discussed concerning the evaluation metrics used in this work. The handover-based metrics and data transmission-based metrics are discussed.

First, number of handover and handover failure: handover is the process of changing the RAN connectivity from one network to another. In general, 5G is a heterogeneous network that has support for all short-range and long-range data transmissions. Due to the presence of a variety of RAN, the process of network selection is significant in the 5G environment. On the other hand, the vehicles move at a different speeds, so the concept of handover is incorporated. This work proposes handover prediction and selection of networks, which was not performed in previous work.

In the existing study of the TOPSIS algorithm, ANDSF, and V2I-MoLoHA methods, the network was selected from the computation of one or more metrics once it receives the request from the vehicle. While in the proposed work, on receiving a vehicle request, it predicts the requirement of handover, and then it selects a network only if needed. The prediction process using dynamic Q-learning leads to minimizing unnecessary handover and then F-CNN leads to improve optimal network selection. Hereby 45 to 50% of the performance of handover is improved than the existing algorithms.

Second, throughput and delay: throughput and end-to-end delay are the important parameters that are used to measure the performance of the proposed work with the previous algorithms. The selection of routes using an optimization algorithm with vehicle metrics can identify an optimal route. As a result,

40 to 45% of the throughput is improved than the previous methods. The improvement in throughput will also impact other network parameters. Then the end-to-end delay is 10 to 15% improved than the previous algorithms.

The proposed algorithms for handover decision, network selection, and routing have a major impact on the performances of the network. This work takes into account the most essential metrics for making a decision and network selection. As a result, the proposed work achieves better performance when compared with previous work of handover.

Conclusion

We have proposed three algorithms for making handover, network selection, and routing in the IoV environment due to the presence of multiple radio access networks. The data transmission requirement depends on each data type. Dynamic Q-learning algorithm is used for making handovers by computing the dynamic thresholds using Shannon entropy rule, and also determines the need for handover. It is clear from the results that using the dynamic Q-learning algorithm, there is a reduction in unnecessary handovers. Appropriate selection of network is achieved using fuzzy-CNN that processes multiple requests simultaneously and enables to considerate multiple parameters to select the network. Besides, a routing algorithm is proposed that forms V2V pairs and selects the best route using a jellyfish optimization algorithm to reduce end-to-end delay, and packet losses. The objective function is defined using vehicle metrics, channel metrics, and performance metrics. The simulation results have shown the superiority of the proposed work considering mean HO, HO failure rate, throughput, delay, and packet loss as the evaluation metrics. The evaluation of switching delays between multiple RAT is the future scope of our work.

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