# Dynamic Q-learning and Fuzzy CNN Based Vertical Handover Decision for Integration of DSRC, mmWave 5G and LTE in Internet of Vehicles (IoV)

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***Abstract***—Internet of vehicles commonly known as IOV is a newly emerged area which with the help of internet assisted communication provides the support to the vehicles. Due to the access of more than one radio access network, 5G makes the connectivity ubiquitous. Vehicle mobility demands for handover in such heterogeneous networks. Instead of using better technology for long ranges and other types of traffic, the vehicles are using devoted short range communications at short ranges. Commonly, networks for handovers were used to be selected directly or with the available radio access it used to connect automatically. With the help of this, the hand over occurrence now takes places frequently. This paper is based on the incorporation of DSRC, LTE as well as mm Wave on Internet of vehicles which is integrated with the Handover decision making algorithm, Network Selection and Routing. The decision of the handovers is to ensure that if there is any requirement of the vertical handovers using dynamic Q-learning algorithms in which entropy function is used to predict the threshold according to the characteristics of the environment. The network selection process is done using Fuzzy Convolution Neural Network commonly known as FCNN which makes the fuzzy rules by considering the parameters such as strength of its signal, its distance, the density of the vehicle, the type of its data as well the Line of Sight (LoS). V2V chain routing is presented in such a manner that V2V pairs are also selected with the help of jellyfish optimization algorithm considering three metrics – Vehicle metrics, Channel metrics and Vehicle performance metrics. OMNET++ simulator is the software in which system is developed. The performance evaluation is done according to its Handover Success Probability, Handover Failure, Redundant Handover, Mean Throughput, delay and Packet Loss.

***Index Terms***—4G LTE, DSRC, internet of vehicles, mmWave 5G, network selection, vertical handover

## I. Introduction

The newly developed vehicle communication via the access of the internet is called Internet of vehicles (IoV). By combining both Intelligent Transportation System & the Internet of Things, Internet of Vehicles is formed. There are two types of vehicle communications one is V2V and the other one is V2I. V2V stands for vehicle to vehicle and V2I stands for vehicle to infrastructure. Secure as well as the un-secure data is transferred by the vehicles at different data rates. Secure data is related with road accidents or road traffic. While the unsecure data is related with video streaming or gaming etc. 5G technologies which comprises of wide range of radio network access[1]-[4]. Some of its examples include Wi-Fi, LTE etc. In other words vehicles communication is backed by both safety as well as non-safety data transmission. DSRC is used by the vehicles which help in enabling Low Latency Communication for the vehicles with short distance. Primarily, IEEE 802.11p is used in processing of the Internet of vehicles which is only convenient for periodic data transmission but not suitable for serving spectrum usages, long data transmission as well as large data transmission. Just because of this reason internet of vehicles has now collaborated with 5G mm Wave that produces high data rate for transmissions. One of the main disadvantages of mm Wave is its blockage because it lacks to penetrate through the objects [5], [6]. The combination of IOV and 5G provides with very high speed data transmission and pervasive connectivity for all the vehicles. Moreover, LTE helps in supporting long distance communication. Although each network access has got some advantages and disadvantages.

In vehicles, the integration of Radio access networks with different terminals helps in switching between RAN. This procedure of switching between one networks to another is called Vertical Handover (VHO) [7]-[9]. 5G technologies consist of three types of cells which are micro, femto and macro cell. Each cell containing different RAN. All the 5G devices promote mobility management and in most of the cases each cell contains more than one RAN. Therefore, it requires best network selection. The process of network selection criteria is such that Multi Criteria Decision Making Algorithm (MCDM) are used in it [10], [11]. This type of algorithms takes helps from multiple parameters and then go for the decision making process. The Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) and others. Such types of algorithms are also very popular. Internet of Vehicles empowers to permit information transmission of parkway and metropolitan roadways in a self-governing vehicle. As the vehicle density increases the no of vertical handovers will increases as well and vice versa.

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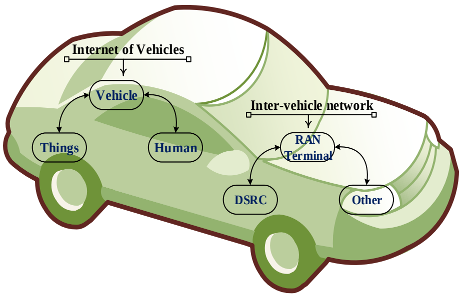


Fig. 1. Vehicle in IoV

The Fig. 1. Shows the development of a vehicle in IOV that adjusts for between vehicle organization, between inter-thing network and between human organizations. To access each RAN, vehicle network adjusts with the utilization of terminals in vehicle. The vehicle is designed in such a way that it has IEEE standard with more than one antenna. The help of various RAN advancements needs to choose an organization when at least one RAN is available in the inclusion range. Through optimization, network selection process can also be presented or even with the help of reinforcement learning methods [12], [13]. An algorithm that can do the decision making process according to the environment is known as Q-learning. The vehicles starts moving at high speed in internet of vehicles so there are rapid changes in its connectivity and its topology. The data transmission which uses DSRC relies on the routing whenever there is change in topology [14]. The procedure of data transfer between sources to its destination with the help of relay vehicles is called routing. With the help of Q-learning, deep reinforcement learning and sweep algorithms, the routes are being selected [15]-[17]. In routing, the vehicles in a course are favored by assessing vehicle based measurements as traffic, vehicle limit, unwavering quality, portability and others. According to the metrics, the path or the route is first analyzed and then the packet forwarding is carried out on that route. This procedure of routing is exposed to some challenges as geography changes, time utilization in course determination etc. The algorithms and other methods are designed in such a way so that these issues can be sorted out. The main objective of this paper is to reduce the unwanted handover while there is a dire need of high bandwidth when the data type is changed. This research basically focuses on a learning based method which helps in deciding that whether there is a need for the handover and which network will be best suitable for it. In this manner, the number of unwanted handovers is reduced. Moreover, V2V routing is formed to incline toward a course for transmission of information with limited re-transmission. In order to overcome this issue from all the available routes an optimal route is chosen through the optimization algorithm. This task main focus is on two things. Firstly, to limit the unwanted handovers and secondly to limit the no of re-transmissions.

The summary of this paper main contributions are as following:

- IOV with 5G technology is diversified that grants LTE as well as mm Wave communication. Every single RAN has got its own advantages and its supports specific data type. So, handover the process only that time when high bandwidth transmissions are required.
- To reduce the no of handovers first the decision making process is done to determine the no of handovers by using Q-based algorithm. This choice relies upon the environment - vehicle speed and signal strength are the two metrics.
- The procedure of network selection by using Fuzzy Convolution Neural Network in which multiple metrics such as distance, type of data, strength of signal, line of sight are considered. To make this selection process procedure faster and quicker convolution neural network is taken into account.
- By using jellyfish optimization algorithm that measures channel, vehicle and its performance metrics V2V chain routing is determined.

The remainder of this paper is coordinated into following areas as Section 2 tells us about the research work and methods which are previously done. Section 3 tells us about specific issue description. Section 4 is based on the proposed algorithm of the handover, routing as well as the network selection. Moreover, Section 5 tells us about the results based on the experimental analysis. Section 6 is based on the conclusion with future research directions.

## II. Related Work

### A. Prior Works on Handover

The authors [18] have suggested a cluster based handoff and proposed dynamic edge-backup node (DEBCK). The vehicles out and about path were clustered and the reinforcement hub was the one that prepare for handoff. Here, the choice of handoff by the vehicles was made by the cluster head and the backup mobile edge vehicle. Storage, communication and energy are the three major parameters which are being considered for handoff. One of its major disadvantages is its backup failure of mobile edged-node. Moreover, cluster head may result in poor handoff or even payoff is not allowed to perform whenever there is a requirement.

A multi-tier heterogeneous networks with the main focus on network selection utilizing the assessment of the metrics such as Relative Direction Index, Proximity Index, Residence Time Index and Network Load Index[19]. However, According to this metrics, the proximity index denotes the trajectory of the vehicle, Residence defines the time acquired by the vehicle to remain within an area. Moreover, in this work, the vehicles were shortlisted from the assessed metrics and afterwards the residence time was estimated. Further, the network was selected from the ranking list. As per this work, all the handover mentioned vehicles will perform network selection irrespective of strong network connection.

In addition to this, A Highway vehicle communication sends with mm-Wave BS for communication [20]. The problem of blockage was due to Non Line of Sight. Hence, this estimates Signal to Interference Noise Ratio (SINR) and outage probability. It also involves DSRC radio access and the mm-Wave, the user selection depends on blockage density. However, over here we have the static edge for SINR but the extent of sign in each radio access differs. [21], The authors have suggested multi-metrics utility-based system selection methodology. Multiple metrics are known as energy, signal intensity, network cost, delay and bandwidth. Moreover, the weight value is computed by gathering available network list and computing energy efficient for each network. The network is selected from the score value and the user demand and hence, a sequential process if performed for each request one after the other. On the other hand, a two-sided one-to-many coordinating calculation was suggested by the authors [22]. Analytical Hierarchy Process (AHP) was being used to process the weight taking into account the type of service. The two services are known as voice and video. After computing weight values, the coordinating were being done to recognize the Quality of Experience (QoE). This process resulted in building the quantity of handover when the vehicle density rises. In addition to this, a game approach [23], was highlighted for network decision utilizing probabilistic strategy. Also, the threshold limit was computed and after this, the handoff possibility was processed to perform handover. At the time when the decision was taken to perform handover; game based network selection was implemented. Thus, the major constraint of using game hypothesis is that it works on judgments and furthermore, the initial thresholds were fixed static. Furthermore, the paper [24], pays attention on handover and routing. A handoff protocol was used, that processes Link Expiration Time (LET) for identifying the network among the vehicles. The partner selection protocols make it feasible to choose an Optimal Partner Node (PN). However, at first, the course was regulated from GPS data and then, after this route partners was selected from the vehicular LET using the data generated from the traffic. Likewise, the vehicle having more LET will be selected as ideal PN in the course. In this process, just a single metric is taken into consideration for selecting a course between source and destination. On the contrary side, if an opposite moving vehicle with more LET isn't selected as PN and subsequently it additionally requires taking into consideration other parameters as well.

### B. *Prior Works on Routing*

Vehicles carry out routing by selecting relay vehicles among the source and destination since the range of DSRC is less and consequently it can't connect with the vehicles having longer distance. In [25], Ant Colony Optimization (ACO) calculation is being used to shade the vehicles. This calculation shows two cycles as the development of the arrangement and the update of pheromone. Coloring was done in order to give a similar color to the vehicle having same objective. According to the pheromone values, the course was being selected in this process. However, this process didn't take into account the huge boundaries of vehicles in calculation of the pheromone value which selects the route for transmission. Thus, the authors [26], have suggested a Cluster based Adept Cooperative Algorithm (CACA) that typically focuses around the QoS measurements. Hence, according to this process, the way toward grouping takes place and a head of cluster was being selected. This process sticks to use the Optimized Link State Routing (OLSR) convention with the Multi Point Relay (MPR). Thus, this selection shows the portability factor, distance reach and Quality of Path (QoP). Moreover, the vehicles that execute these parameters were selected as MPR and after this, the convergence vehicles were not used further. By doing this, a path was selected between the source and objective vehicles. The resolution of MPR isn't skillful as the vehicles move at fast. Thus, be that as it may, MPR is taken into consideration; the vehicle will use just one as its hand-off for communication.

Apart from this, a Multi-Criteria Decision Making Algorithm of AHP was made so that the preference can be given to the vehicle traffic and the coalitional game (CG) that was being used to identify the link among the transfer vehicles, further, selection of relays takes place by the heuristic[27]. The fundamental objective of this process was to solve Ling-of-Sight (LoS) problem. The already used AHP calculation subjects with the rationality problem in giving preferences to the traffic of the vehicles. Therefore, it is not possible to give reliable and proper scoring to each vehicle that further results in helpless selection of transfer. A Delay-Aware Grid-Based Geographic Routing (DGGR) was presented in [28] having the ability to function as a Road Weight Evaluation (RWE) plan alongside division of Grid Zones (GZ). The RWE scheme prefers about two primary data as traffic and connection. Moreover, this process further selects Intersection Backbone Node (IBN) along with Road Segment Back Bone Node (RBN). The road weights were computed from one hop and multi hop delays. This leads to the system being divided into grid zones and there is also an intra-grid transmission and inter grid transmission. Furthermore, the source vehicle scatters the data from which an ideal path was being selected from delay metrics. This process regulates to use the convey and-forward technique for routing. Thus, the delay was the only metric that was considered for selecting a course which isn't satisfactory.

Likewise, routing was done which was based on optimization algorithm. In [29], a hybrid optimization that combines monarch butterfly and grey wolf enhancement for network selection. In this, the parameters that are considered for route selection are different costs that are determined for congestion, collision, travel and Quality of Service. However, Fuzzy member functions are applied for Quality of Service (QoS) Prediction. Firstly, the butterfly calculation was being involved in it and afterward the dim wolf was done for updates of positions and selecting optimal paths. The problem in dark wolf optimization was not able to perform good thus, there was a low accuracy. Moreover, Fuzzy Logic was further used for choosing paths by estimating the link and throughput [30]. In addition to this, the quality of the link was based on the position, direction and expected transmission count. So, according to the fuzzy weight, the output of the next hop relay selection was being done. However, this work suffers from mobility issues in vehicular communications. For the significant restrictions in the prior works, the work being suggested overwhelms the primary problems in routing as well as in handover and network selection. However, solution to these problems is listed in this research paper.

## III. Problem Definition

In this section, the problem identification in the handover part, selection of the network and routing has been stated through the previous research works. The author [31], is basically using DSRC for the communication of V2V and mm-Wave for the communication purpose of V2I. For DSRC communication, it basically uses Reinforcement Learning method like Q-learning which requires high priority and time aware V2V communication. Similarly, TOPSIS, K-Nearest Neighbor (K-NN) and AHP was being used for handoff decision utilizing bandwidth, network cost, preferences, connectivity and Signal to Noise Ratio (SNR) [32], [33].

- TOPSIS calculation follows the distance rule which results in differentiation from the norm in positioning possibilities. This calculation is exposed to rank reversal problem which either involves or rejects the request for preferences. Moreover, for the betterment of this problem, it acts poor for making vertical handover selection.
- According to the result of the position, the handover is acted upon by the vehicle. In any case, the need for handover isn't evaluated. Besides this, if all the vehicles need handover, at that point the TOPSIS must be performed individually for every vehicle as the parameters differs for every vehicle.
- The usage of k-NN for handover selection is not effective, since the k-NN calculation gives more precision in result just when the information quality is better. Additionally while the appearance of information is in large sum then the calculation paves a way down to measure and subsequently it needs some time to make handover selection.

The information transfer by ways for these two measurements isn't satisfactory, since there might be blockage that causes NLOS issues. This is basic in mm Wave and henceforth for sending the other channel and vehicle parameters are required.

- The usage of AHP isn't effective as it needs preparing of the information and after that it can select the most appropriate path. However, here according to the current conditions of the vehicles the path should be selected and furthermore the development of vehicles won't be similar on every district. Likewise, the expansion of new models is difficult in this calculation.

The method of routing was performed utilizing Dijkstra calculation and random transfer selection for information sending [34]. Moreover, nature of service parameters was diagnosed to choose a course. The vehicles move dynamic thus the geography is controlled by the graphs construction. However, major issues under routing are listed below:

- The parameters for the graph are depending on the prior transmission of the vehicle, while the transmission of the vehicle is dependent upon the channel metrics. The graph that is using these metrics can't ignore the strength of a vehicle with its neighboring vehicle and due to this, it creates successive frequent handover.

In heterogeneous networks, the graph maintenance is complicated as the devices very with mobility and hence it is essential to use larger resource and dynamic processing of graphs

Poor selection of network because of randomly selecting networks considering single parameters. The main QoS parameters considered in this work are Bandwidth, Delay etc. It considers any one from this and subsequently, minimizing QoS in the network.

All the above defined problems were solved in this proposed work by proposing Novel Handover Decision, Network Selection and Routing. The Algorithms preferred in the solution enables to improve the performance of the proposed work.

## IV. Proposed System

This particular section is divided into four sub sections to briefly explain the environment and to extend individual algorithm in this planned research task. Handover decision, network selection and routing are the three main processes that are specified in this particular section.

### *A. System Model*

The proposed IoV coordinated 5G organization is planned with vehicles. The environment consists of 5G base stations with the help of mm Wave, Base station of LTE, vehicles and RSU. Below are some of the definitions for every identity that participates in this system:

**Definition 1: Vehicle –** There is a restricted path for vehicles in which it moves, for example, a road lane in which its route is already pre-defined on the map. The speed of the vehicle depends on the type of vehicle. With the help of build-in GPS in vehicles the information of their latitude and longitude is collected. The speed and location of the vehicle are dynamic. Vehicles specifically use DSRC and other advance RAN for the transmission of safety and non-safety data.

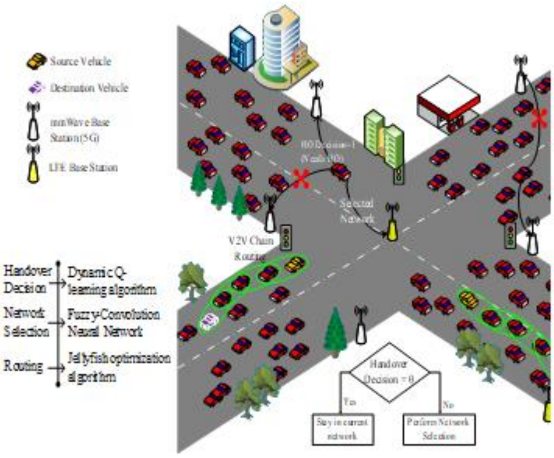


Fig 2. Proposed system model

**Definition 2: RSU –** RSU is utilized in IOV for performing correspondence with the framework. RSU is static in the surroundings and it also helps in enabling DSRC in vehicles.

**Definition 3:5G mmWave Base Station (BS) –** This type of entity is also static and it helps in the performance at high speed as well as short range communication. It also helps in solving the lack of spectrum issue.

**Definition 4: LTE BS –** This BS is likewise static and it permits significant distance correspondence with higher transmission capacity and similarly high range productivity.

In Fig 2 the proposed framework model is represented which consists of each and every identity that is mentioned above into the system. There are 'n' number of moving vehicles on the road lane and has its own direction. Handover processes, and network selection are the three main processes of this task. But considering this task the decision of the handover will be taken by the vehicle only when the link of current base station is not satisfactory. But during the moment when there is a dire need of safety application transmission the network selection process during that moments becomes one of the parameters alongside the thought of data type. The decision through which the need for the handover is identified is known as the handover decision and it is performed on the availability of the network. Dynamic Q-learning is used for the handover decision making in which the threshold is already set according to the environment. A network is selected from the Fuzzy Convolution Neural Network (F-CNN) if the network needs to be performed. The fuzzy rules are already mentioned and explained and are used in CNN. At that point routing occurs by utilizing an optimization algorithm of jellyfish calculation that selects V2V combination between sources to objective thus it is called V2V chain routing. The procedure is performed according to the vehicles need.

*B. Handover Decision*

The Handover Decision by the Dynamic Q-learning. By dynamic we mean that the threshold used considering the availability of the network. Vehicle speed and its strength are the two main important parameters that are considered. Both of these parameters are dynamic and as the speed of the vehicle is dependent on the traffic density and for every RAN which is accessible the signal strength is different. Moreover, the speed of the vehicle will either increase or decrease within the speed limit according to the ability of the vehicle. But, the signal strength of the RAN is totally dependent on its availability also, subsequently the signal strength value whenever set dynamic as indicated by the reach. For example in Range R1 the MM coverage could have been better than the LTE. While in Range R2 the LTE will be much better when compared with MM wave. So because of this a threshold for signal strength is made below in dynamic with the help of Shannon entropy.

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

The Shannon entropy for signal strength is stated as S(ss), that consists of ss esteems for DSRC, mm Wave and LTE between the range of (- 30dBm to-70dBm). In condition P (ss) shows the possibility of the signal strength which is available strong. Also, the vehicle's area will give the BSs that come under it and at that point the threshold is being set.

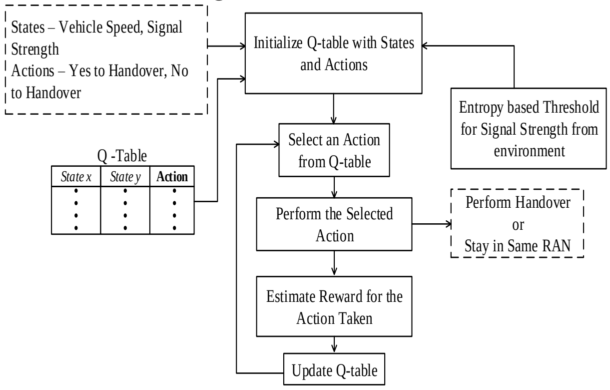


Fig. 3. Workflow of dynamic Q-learning

The boundaries signal strength and vehicle speed is the states that are taken into consideration while making a move for handover. Let Q(S, A) show the state S and activity A that are being based on the Q-values. There will be two boundaries for every state S and this standard resolves and update the Q(S, A). Moreover, in this reinforcement learning algorithm, an agent gets involves to agree upon the change of states and the activities related to it Furthermore, the specialist figures awards from each move activity by its inspection. The temporal difference update rule is listed below:

$$Q(S, A) + \alpha(R + \gamma Q(S', A') - Q(S, A)) \rightarrow Q(S, A) \tag{2}$$

The expression Q (S', A') describes the next state and activity R as the reward given by the agent, and $\gamma$ is the discount factor that is [0-1] while α is the learning rate [0-1] i.e.it shows the progression length to estimate the (S, A). The step is being taken using ϵ-greedy approach while ϵ shows epsilon. However, under this strategy, from the initial phase the agent inclines toward activity randomly due to less investigation in the climate. Moreover, later the pace of epsilon gets reduced and the agent begins to take steps according to the environment. Despite the fact that the selection is random in the starting phase, the dynamic edge empowers to results to make appropriate selection. Also, the pseudo code for dynamic Q-learning describes about preparing of this calculation for handover's decision.

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 $\epsilon$ −greedy policy
    obtain Q-value from Q-table
    perform action $A \rightarrow V_1$ // Action taken by vehicle 1
    compute $R$ and next state $S'$
8. update Q-table using equ (2)
9. update $S' \rightarrow S$
10. end

### C. Network Selection

With network selection we can choose networks from the available RANs. For network selection, F-CNN calculation is applied. The CNN is coated with the layers of convolution, max-pooling and completely associated layers. These layers are then used with the fluffy guidelines that are defined from the measurements signal strength, distance among BS and vehicle, vehicle thickness in serving BS, Data type (Safety or Non-Safety) and Line of Sight (LoS). The definition for each metrics is as follows:

**Definition 1: Signal Strength –** SSNR is described by the signal strength which gives the amount of signs. Moreover, noise and sign will be made by the channel and the more the noise, the channel becomes weaker for the transmission. The SNR ($S_r$) is described from power of signal $P_s$and noise $P_N$separately. The formula is stated below:

$$S_r = \frac{P_S}{P_N} \tag{3}$$

**Definition 2: Distance among BS and vehicle –** Euclidean distance is used to assess the distance among BS and a vehicle. This measure describes the steadiness of connection, as with more distance the connection will become unstable and a reduction in distance will make the connection more strong. Euclidean distance is calculated using the formula below:

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

To calculate the distance, the coordinate points of the BS and vehicle is utilized. Distance $D_{(L_{BS},L_V)}$ is resolved from the BS area coordinates of (x, y) and vehicle area coordinates of $(x_1, y_1)$ separately. The location of BS is fixed thus it needs to know that just the coordinates of vehicle facilitate for distance assessment.

**Definition 3: Vehicle Density –** The thickness of vehicle $V_D$ means the quantity of vehicles that are associated with that specific BS.

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

$N_{CL}$ And $N_{NL}$ shows the quantity of associated connections and number of new connections.

**Definition 4: Data Type –** there are two types of information associated with the vehicles i.e. if they are safety or non-safety. In this work, safety is meant as 0 and non-safety as 1. Traffic data and high speed vehicle data are the messages linked with the safety. This type of information has higher need in transmission than the non-safety information.

**Definition 5: LoS –** Line of sight basically describes the immediate contact between the vehicle and BS with no restrictions that stops the signs. For transmission LoS is just preferred while signals in Non-LoS aren't preferred.

TABLE I: FUZZY RULES

| Rule number | Input | | | | | **Output** |
|---|---|---|---|---|---|---|
| | $S_r$ | Distance | $V_D$ | Data type | LoS | |
| 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 |

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The five definitions stated above help in the making of fuzzy rules. The fuzzy rationale manages the decisions by the rules described in Table I. Thus, we follow this rationale into CNN by considering network measurements and then further select network for each vehicle. Also, the CNN can deal with different information at a time, so a bunch of vehicles that needs handover is considered as the inputs. The mm Wave signs will be picked for traffic in case when the LoS is there since restrictions of mm Wave prompts bad performance, however, in case of blockage the vehicle selection will be 4G LTE.

The fuzzy rationale strategy works with the IF-THEN rules in interference engine. The information is in fresh qualities that are changed over into fuzzy set. According to the fuzzy guideline the interference motor builds membership function among [0, 1]. The fuzzy rationale activities are incorporated into CNN. Fig. 4 portrays the built fuzzy rationale with CNN. The yield High (H), Medium (M) and Low (L), means as follows,

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

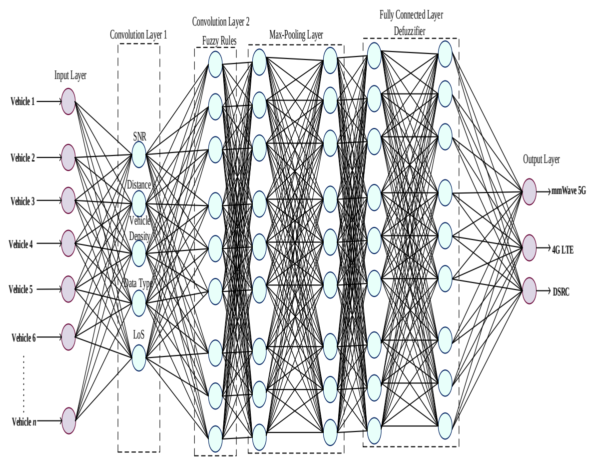


Fig. 4 Fuzzy-Convolutional neural network

In the convolution layer, the arrived vehicle requests will compute every parameter; it learns the boundaries and then after this feeds to max-pooling layer. Moreover, the fuzzy layer is applied into second convolutional layer. As indicated by the fuzzy layer, the output is anticipated and given to fully connected layer. Also, this layer then changes the fuzzy set into crisp output. Subsequently, the output layer results with the chose network for each vehicle. A pseudo code below is shown dependent on the work flow of this fuzzy CNN algorithm.

Pseudo Code 1: Fuzzy-CNN

**Input** – Vehicle $Req$
**Output** – Network Selection ($N_S$)
1. begin
2. $V(Req) \rightarrow N_S$ //vehicle requests for selecting network
3. for each ($V \rightarrow SNR, D, Density, DT, LoS$) // 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

In addition to this, the usage of CNN will give result for various vehicles simultaneously by parallel processing technique. The proposed Fuzzy-CNN makes out of 32 standards, which is described by five parameters. Since the CNN can measure in-equal, the 32 number of rules will be prepared in the convolution layer. As indicated by the chose network, the mentioned vehicle will hand over from current network to the network that is being targeted.

### *D. Routing*

V2V Chain Routing is the cycle that performs routing by choosing V2V sets from the source vehicle to the objective vehicle. For this purpose of communication, the vehicles use DSRC signals. The association of V2V sets will frame a chain thus we give this as V2V chain routing. Also, the V2V sets are chosen by using the jellyfish advancement calculation. Under this advancement calculation the target work is described using the thought of three arrangements of measurements as channel measurements (SNR (s_r), link quality ($l_q$)), vehicle metrics (Speed ($s_p$), Relative Direction $R_d$ and vehicle performance metrics (Delay ($D_l$), throughput ($T_p$)).

Furthermore, Jellyfish calculation depends on the conduct of jellyfish on ocean looking for their food. In this enhancement, the objective work is described from channel metrics, vehicle metrics and vehicle performance metrics. The population for example number of accessible way between sources to destination is introduced. From the accessible ways this calculation chooses an ideal way. To improve the convergence rate, control time is assessed. In the calculation, the jellyfish looks for food, while in our work the ways are the jellyfish which looks for an ideal way. However, the nature of food is figuring in conventional jellyfish calculation, while in this work, we register the nature of way from the metrics and then further select an ideal way.

At the point when a vehicle needs to advance any street traffic data, the safety message it utilizes DSRC which is effective to perform at short distance with low latency. However, Jellyfish calculation depends on the conduct of jellyfish on sea looking for their food. The jellyfish development is either active or passive and that basically depends on the ocean current or swarm. Furthermore, to switch between these two developments, a time control instrument is utilized in this calculation. The time control c (t) is detailed from cycle and the random values are portrayed in the following:

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

When,

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

$rand(0,1) < (1 - c(t))$, then active motion (7)

In IoV, the vehicles move quicker at less traffic area for example in the cases of highways and move more slow in the areas where there is a lot of traffic for example metropolitan cases. Here the jellyfish is the vehicles and the ocean is the road lane where the vehicle moves in various speed.

The current direction of the ocean is stated as $\overrightarrow{OC}$ and it is numerically given below:
Let,

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

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

The terms $V_p$ population of the jellyfish in ocean, for example population of vehicle according to this work. $X^*$ indicate the best area, μ is the mean area and $e_c$ is the attraction factor, here the attraction of on objective. At that point the target work is described to choose a best course. This capacity of is figured below:

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

Nevertheless, in this work a bunch of boundaries are taken into consideration that is represented as Ms. The measurements postponement and speed ought to be least, while the wide range of various boundaries can be of higher value, the vehicles that fulfill this OF has higher chance to choose the route. Here the OF is applied for the total route, since this work chooses an ideal route from the accessible routes. The measurements are assessed from the channel,

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

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

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

The criteria$P_f$, $P_r$ indicates the quantity of the packets that are being forwarded and also the packets that are received in return in the similar connection between two vehicles, at that point (la, ln) speaks to the (latitude, longitude), so the location of the vehicle is $(la_v, ln_v)$ and the following hop location is $(la_{np}, ln_{np})$ and r is the range for example inclusion of the vehicle. The assessment of deferral is registered from $P_L$, $b$ having the packet's length and bit rate for example transmission speed in bits every second. According to the described objective work, the ideal route is chosen utilizing this jellyfish streamlining calculation.

The vehicles use DSRC to perform correspondence over the chosen route. The exhibition of the proposed HO, network selection and routing is assessed in next segment.

## V. Experimental Evaluation

This section is categorized into three sub-sections as simulation setup, comparative analysis and result discussion. The experiment details and the parameters area details in this section.

### A. Simulation Setup

This proposed work is simulation using network simulator, since vehicles are connected in network [35]. The Objective Modular Network Testbed in C++ (OMNeT++) that combines with SUMO which gives real time map based architecture. The OMNeT++ 4.6 version is installed on Windows 7 operating system having 32-bit. Along with this JDK 1.8 is used for SUMO version 0.21.0.

TABLE II: Simulation Specifications

| Parameter | | Range / Value |
|---|---|---|
| Simulation Area | | 2500m × 2500m |
| Number of Vehicles | | 100 |
| Number of 5G mmWave BSs | | 2 |
| Number of 4G LTE BSs | | 2 |
| Vehicle mobility type | | Linear mobility |
| Vehicle Speed | | 10 to 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 | | 1000 seconds |

The important simulation specifications of the proposed research are shown in Table II. Apart from these parameters, there also exists other default specifications. That is to say, it will include LTE, mmWave 5G and DSRC configurations on vehicle. As per these specifications, the proposed handover, network selection and routing is performed.

### B. Comparative Analysis

Comparative analysis gives the acquired outcomes in similar charts. This proposed work is contrasted and past research work [31] in which handover network determination choice depended on TOPSIS calculation. It is a multi-models dynamic calculation that measures with more than one criterion. The boundaries that are assessed in this work are handover success probability, handover failure, unnecessary handover, throughput, delay and packet loss...

#### 1) *Handover success probability and handover failure*

These both are vital in approving the presentation of a handover technique. The success probability is described as the likelihood of progress to perform handover a vehicle starting with one network then onto the next while the handover failure describes the quantity of failed handover. The MCDM is included for decision making to handover. The increment in handover success probability means the better exhibition of the proposed calculation. In past work, TOPSIS was utilized for the choice of network that neglects to perform appropriate positioning.

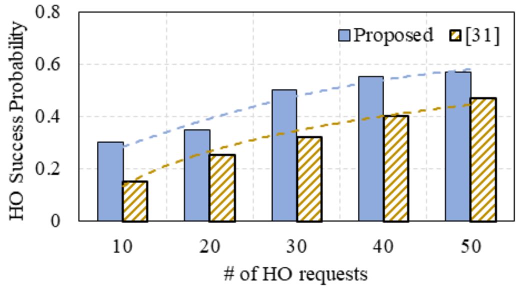


Fig. 5. Comparison of HO success probability

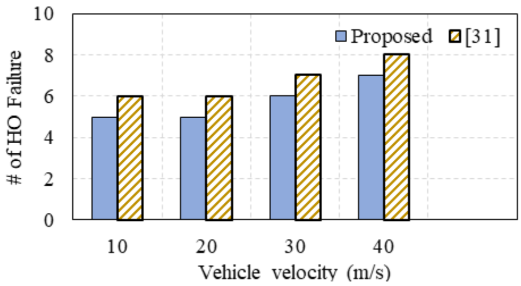


Fig. 6. Comparison of HO failure

The Fig. 5 and Fig. 6 shows the achievement success and failure individually. This outcome shows that the choice by dynamic Q-learning and F-CNN have better determination in handover. The success probability of proposed work rises according to the rise in HO demands and henceforth this network selection is reasonable for large scale environment. Then again, the increase in success probability prompts to reduction in the quantity of HO failure counts. As indicated by the speed up, the handover failure happens. The proposed handover is around 10% better than the past network selection calculation.

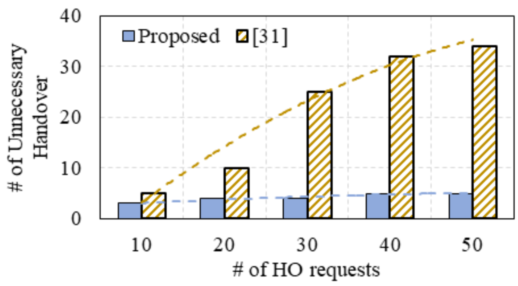


Fig. 7. Comparison of unnecessary HO

In the assessment of the HO's performance, this work additionally looks at the event of number of unnecessary handover. According to the expansion in the quantity of handover demands, the network performs to approve the requirement for HO and network's selection. The poor performance of TOPSIS results with rise in number of pointless HO as demonstrated in Fig. 7. The primary reason for the degradation of handover is shown underneath:

- Selection of boundaries to choose the appropriate network which needs to consider vehicle measurements just as the BS measurements.
- The number of handover rises because of the absence of approving the vehicle with respect to the requirement for handover. These results to rise in the number of unnecessary handover which likewise requires huge resource blocks for performing the calculations.

*2) Mean throughput and delay*

Throughput and delay assesses the network performance concerning the capacity of the characterized calculation for data transmission. The throughput boundary is characterized as the measure of information that is moved from a vehicle to another inside the predetermined measure of time in agreement to the data rate. The higher the mean throughput, at that point the impact of routing is better. Essentially, delay characterizes the measure of abundance time taken by a vehicle to move the data. The higher the estimation of delay, it mirrors the poor performance of routing.

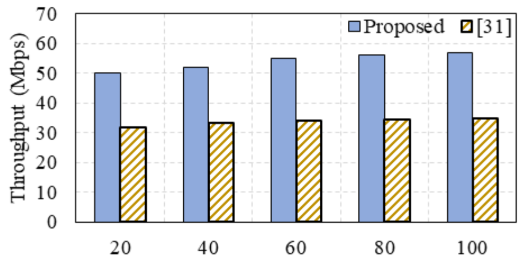


Fig. 8. Comparison of throughput

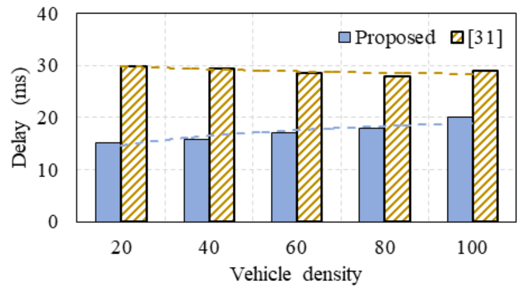


Fig. 9. Comparison of delay

The graphical plots for throughput and delay is depicted in Fig. 8 and Fig. 9 that compares proposed with existing wok. On average, the throughput difference of about 20Mbps, for upto 100 number of vehicles. In proposed, increase in the result of throughput is due to the optimal selection of route using jellyfish algorithm that considers vehicle metrics, channel metrics and performance metrics all together in the objective function. Also this is the major reason for the minimization of delay when compared with previous work. The average delay difference is upto 12ms for about 100 vehicles in the network. The graph shows minor growth and drop in the delay, so even the further increase in number of vehicle will not reflect on delay since the route is selection optimal.

*3) Packet loss*

Packet Loss is a boundary that characterizes if the data transmission is compelling. The small loss of packet will show the better choice of route for data transmission. The parcel loss in routing happen for various reasons, consequently the Packet loss rises when there is a break in connection because of high mobility, poor signal constraints and high density.

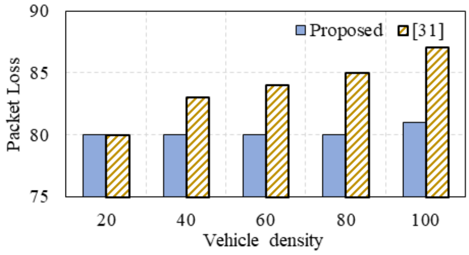


Fig. 10. Comparison of packet loss

In proposed work, the route determination is by jellyfish calculation that thinks about vehicle metrics, channel metrics and vehicle execution metrics which is proficient in the choice of ideal route. Additionally the thought of metrics is significant in routing. The graphical aftereffect of parcel loss is shown in Fig. 10, where the proposed work is thought about and accomplishes lesser loss than the past routing. According to the vehicle thickness builds, there will be higher number of transmissions, so there can be a rise in packet loss. Be that as it may, the vehicle thickness expands it likewise considers packet loss yet in proposed work, the ideal selection of course prompts deal with the packet loss.

### *C. Result Discussion*

The proposed work of IoV incorporates DSRC, LTE and 5G mm Wave in which we center on handover because of the involvement of more than one RAN. In light of the sort of the data to send, each network gives better data rate for productive transmission. In Table III, the proposed work calculations and their effect on the performances are portrayed. The proposed calculations for handover decision, network selection and routing majorly affect the network's performance. This work assesses the most fundamental metrics for settling on decision making as well as the network selection. Accordingly, the proposed work accomplishes better execution when contrasted with the past work of handover.

TABLE III: PROPOSED SOLUTIONS AND THE PURPOSE

| Process: Algorithm | Purpose | Result |
|---|---|---|
| Handover Decision: Dynamic Q-learning | • Learn the current environment and makes decision.<br>• Signal characteristic in a dynamic environment like vehicle is not fixed due to mobility, so handover decision is taken by learning. | • Reduces unnecessary handover by 25% than existing<br>• Reduces handover failure by 2% than existing. |
| Network Selection: Fuzzy-CNN | • Selection of network is done one by one is not efficient since the vehicles move at high speed. So to make network selection for multiple handover requested vehicles, we have used this parallel processing.<br>• This considers multiple criteria to select a network. | • Improves handover success probability. |
| Routing: Jellyfish optimization | • The vehicles have high moving speed so the path selection is performed by this simple algorithm in which multiple parameters are used.<br>• It is able to select optimal route at high mobility as well as low mobility. | • Improves throughput by 15 to 20 % than existing.<br>• Minimizes delay and packet loss. |

## VI. CONCLUSION

In this paper, the IoV climate is developed with vehicles that is furnished with three terminals as DSRC, LTE and mm Wave 5G. The data transmission prerequisite depends for every information type. However, due to various RAN, the cycle of handover is proposed in this work. In the initial phase, dynamic Q-learning calculation is utilized for settling on handover selection with the dynamic threshold calculation utilizing entropy for signal attributes. The utilization of fortification learning calculation for handover choice can get familiar with the climate and settle on choice that results in minimizing the number of pointless handover. At that point the network selection by fuzzy CNN, since it can handle various solicitations that show up at a time. This fuzzy CNN empowers to think about numerous boundaries to select the network. There are 32 fuzzy rules, in view of which the network is being selected. IoV is a large scale network, to address adaptability issue in network determination, the fuzzy CNN is utilized. This calculation can work quicker because of the development of neural nodes that work in parallel. At the point when a vehicle needs to speak with a significant distance vehicle out and about path, a route is chosen. Here DSRC is favored by the vehicles, since it is low latency when speaking with the adjoining hop vehicles. Moreover, a V2V chain routing is proposed for routing that chooses a route utilizing jellyfish advancement and chooses V2V sets in a route and performs information transmission. However, the target work for routing is described from three as vehicle metrics, channel metrics and execution metrics. In this manner an ideal route is chosen for information transmission. The aftereffects of this execution work give better effectiveness as far as handover boundaries just as routing boundaries. In future, this work is intended to reach out with the utilization of machine learning calculation for handover and assess the outcomes utilizing same IoV environment.

## Conflicts of Interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

## Authors Contributions

Authors 1 and 2 conceived of the presented idea and developed the theory and performed the computations. Author 1 has verified the analytical methods. Author 2 has supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

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