Intelligent Reward based Data Offloading in Next Generation Vehicular Networks

Gunasekaran Raja*, *Senior Member, IEEE*, Aishwarya Ganapathisubramaniyan†, Sudha Anbalagan‡, Sheeba Backia Marry Baskaran§, Kathiroli Raja¶, Ali Kashif Bashir‖, *Senior Member, IEEE*

***Abstract*—*Abstract*–A massive increase in the number of mobile devices and data hungry vehicular network applications creates a great challenge for Mobile Network Operators (MNOs) to handle huge data in cellular infrastructure. However, due to fluctuating wireless channels and high mobility of vehicular users, it is even more challenging for MNOs to deal with vehicular users within a licensed cellular spectrum. Data offloading in vehicular environment plays a significant role in offloading the vehicle's data traffic from congested cellular network's licensed spectrum to the free unlicensed WiFi spectrum with the help of Road Side Units (RSUs). In this paper, an Intelligent Reward based Data Offloading in Next Generation Vehicular Networks (IR-DON) architecture is proposed for dynamic optimization of data traffic and selection of intelligent RSU. Within IR-DON architecture, an Intelligent Access Network Discovery and Selection Function (I-ANDSF) module with Q-Learning, a reinforcement learning algorithm is designed. I-ANDSF is modeled under Software-Defined Network (SDN) controller to solve the dynamic optimization problem by performing an efficient offloading. This increases the overall system throughput by choosing an optimal and intelligent RSU in the network selection process. Simulation results have shown the accurate network traffic classification, optimal network selection, guaranteed QoS, reduced delay and higher throughput achieved by the I-ANDSF module.**

***Index Terms*—Mobile Data Offloading, Q-Learning, Markov Decision Process, SDN, I-ANDSF, QoS, Vehicular Network, Road Side Unit.**

I. Introduction

The number of mobile devices such as smartphones, laptops, tablets, etc. has evolved drastically due to emerging trends in data services and the number of users. According to a recent survey [1], people expect seamless internet connectivity anywhere, anytime, even in their vehicles. The massive growth in mobile data traffic demands the availability of high-speed internet services everywhere. This motivates cellular operators to switch from 3G to 4G and currently towards 5G for providing reliable internet access to the in-vehicular environment. By 2021, the number of internet-connected devices are expected to reach 11.6 billion [2] and as a result, the mobile data communication requires increased Quality of Service (QoS). Mobile data traffic will grow at a compound annual growth rate of 42 percent from 2017 to 2023, reaching 100 exabytes per month by 2023 [3] leading to data proliferation issues. With frequent handover in the trending 4G and 5G network, due to the high mobility of vehicles and bandwidth limitations, it is quite challenging to handle both vehicular and non-vehicular users. In this work, we consider the mobile user in a vehicle as a vehicular user and pedestrians or stationary users as non-vehicular users. To handle both vehicular and non-vehicular users, one way is to enhance the capabilities of existing cellular networks by deploying more number of base stations. However, it requires higher OPerational EXpenditure (OPEX) and CAPital EXpenditure (CAPEX) [4]. Some existing standards like Wireless Fidelity (WiFi), small cells such as Femto or Pico cells aim to solve the data traffic proliferation problem [5]. However, sharing of the same licensed spectrum by small cells leads to channel interference issue due to its limited capacity. To solve this channel interference problem, WiFi stands out a feasible solution and helps the network operators to offload cellular data traffic through WiFi hotspots (densely data populated vehicular area).

From the recent survey [6], it is proved that WiFi operates at high vehicular speed for outdoor internet access. Data offloading in a vehicular environment refers to the data traffic generated by vehicular users that get offloaded through the opportunistic WiFi networks. Accordingly, WiFi can be used as an offloading medium not only in homes but also in many public places of Heterogeneous Vehicular Networks (HVNs). HVN integrates WiFi with cellular networks, thereby users from 3G, 4G or 5G networks can utilize the HVN in an efficient manner. This helps in critical safety information exchange among vehicles with the help of Road Side Units (RSUs) deployed on roadside to detect the irregularities and performs similar to WiFi Access Points (APs) [46]. The concept of LTE WiFi offloading plays a vital role in various applications which includes load balancing in HetNets, traffic aggregation for multi RATs, mobility management in Mobile Adhoc Networks, etc.

In Vehicular Ad-hoc NETworks (VANETs), Vehicle-to-Vehicle (V2V) communication and Vehicle-to-Infrastructure (V2I) communication are used to serve safety and non-safety applications. To ensure seamless connectivity for vehicular users, their application service requests are classified into safety and non-safety applications, which in turn help the Internet Service Providers (ISPs) to maintain the overall network performance [7]. Safety applications disseminates critical sensitive information among the network. For example, sudden break warning, congestion warning, collision control messages are some of the crucial messages which do not need communication from the infrastructure and disseminate among V2V network using IEEE 802.11p technology [42]. As

G. Raja and A. Ganapathisubramaniyan are with NGNLab, Department of Computer Technology, Anna University, Chennai, India. (e-mail: dr.r.gunasekaran@ieee.org; aishwarya97.mit@gmail.com).

S. Anbalagan is with Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur, India. (e-mail: sudhaa@srmist.edu.in)

SBM. Baskaran is currently working as a Senior Researcher and 3GPP SA2 delegate with Huawei Technologies, Sweden. (email: sheeba.sinto@gmail.com)

K. Raja is with Department of Computer Technology, Anna University, Chennai, India. (email: kathirolig@gmail.com)

A. K. Bashir is with the Department of Computing and Mathematics, Manchester Metropolitan University, UK. (e-mail: dr.alikashif.b@ieee.org)

safety applications communicate among vehicles, offloading this type of application to RSU network is not necessary. Non-safety applications ensure the comfort of the users. For example, playing online video games, watching YouTube videos, internet browsing are some of the applications, users utilize for their comfortable and sophisticated travel. For non-safety applications, the users request data based on the demand of the application, so it needs interaction with the cellular infrastructure. Non-safety applications continuously send and receive traffic to/from the cellular network [43]. Therefore, it increases the overload and congestion problem in the cellular network. Thus, this classification can be further extended to offload only the non-safety application traffic based on offloading strategies such as opportunistic and delayed offloading [8]. The purpose of data offloading is to increase the per-user throughput by combining network-centric and user-centric parameters to provide seamless handover between licensed and unlicensed spectrum [9]. Opportunistic offloading plays a vital role in providing seamless robust connection for vehicular users. Here, the data offloading is performed when the vehicular user comes into the coverage of WiFi APs and the traffic is transmitted back to the cellular network when the WiFi signal fades away. In delayed offloading, if no WiFi signal is detected within the stipulated time, then automatically the incomplete data transmission gets started using the cellular network when it is available, otherwise, it may lead to data loss or service failure [10, 11].

In HVN, data offloading scheme mainly focuses on the performance and the availability of respective RSU's in case of non-vehicular users. As they have slow movement when compared to vehicular users, they gain a seamless connection from single RSU itself. But in the case of vehicular users, they meet several RSU's with different QoS. So, in vehicular data offloading, the major challenge of users is to select an optimal RSU among the available ones, to perform an optimal decision making when switching from cellular to WiFi network. During this switchover process, the user needs to have guaranteed QoS [12]. Here we summarize the need for data offloading in vehicular networks as follows:

- The congestion of vehicular users in the cellular infrastructure can be avoided by obtaining a connection from cost-effective opportunistic WiFi networks.
- Data-hungry applications will experience better QoS, higher throughput and improved residence time offered by WiFi networks.
- The issue of the available limited cellular spectrum is solved by offloading higher bandwidth consuming applications to WiFi networks with less interference channel 11.

However, unlike offloading non-vehicular users, there exist different characteristic challenges when dealing with vehicular users due to the highly dynamic vehicular environment, fast fluctuating wireless channels, etc.

The key contributions of this paper are summarized as follows:

- An optimal decision of switching process from core cellular network to RSU needs dynamic updating of RSU's location, user's position and the load information of the respective RSU. Thus, with the help of SDN as a centralized controller, a Combined User and Network Information (CUNI) approach is used for intelligent RSU selection process.
- Intelligent Reward based Data Offloading in Next Generation Vehicular Networks (IR-DON) architecture is proposed to perform efficient switch over with the help of machine learning algorithm for offloading.
- In the IR-DON architecture, we propose the Traffic Splitter algorithm which classifies the user non-safety application traffic into core cellular network part and the WiFi or RSU part. Using this algorithm, the amount of traffic to be offloaded is identified and with the help of the proposed Intelligent-Radio Access Technology (I-RAT) selection algorithm, the offloaded part of traffic moves towards the respective RAT.
- The proposed I-RAT selection algorithm is based on Q-Learning and it is used for intelligent RSU selection. This algorithm calculates the reward values of both LTE and RSU available within the user's vicinity and select an optimal and intelligent RAT based on the maximal reward value among them. Thus, the ultimate goal of the user is to maximize the reward value.
- An I-ANDSF module is designed under SDN controller to make an intelligent decision for both traffic splitter and I-RAT selection algorithm. This approach helps the user to increase the overall throughput and reduces the time delay to connect with the best RAT. Thereby, the proposed IR-DON architecture aims to achieve an efficient offloading ratio.

The remaining section of the paper is organized as follows. Related work is presented in Section II. The problem formulation with key challenges and the proposed system model are presented in Section III. Section III also describes the proposed IR-DON architecture along with Traffic Splitter and I-RAT selection algorithm. Section IV and V details the mathematical and performance analysis. Section VI concludes the paper with some related direction to future work.

II. Related Work

In this section, we review the techniques of user application traffic classification, analyze the main strategies of data offloading, provide a comprehensive study of data offloading in vehicular networks and finally we illustrate the objective of the proposed model.

Certain traditional methods to perform traffic classification in HVN are port based and payload based methods. In port based method, each application is assigned different port numbers to identify the specific traffic with the help of Internet Assigned Number Authority (IANA). Due to the enormous growth of Peer to Peer (P2P) applications, this technique fails to register the application with dynamic port numbers. In Payload based technique, for each application traffic, the entire packet is examined by its network characteristics and this is called Deep Packet Inspection (DPI) technique. DPI is majorly used for P2P applications and it solves the issues faced by the application which uses dynamic port numbers but it forces the device to have complete knowledge about the user application that becomes the major drawback. These methods cause severe issue to handle the applications in the encrypted form, where in data sensitive applications, the extensive content analysis is difficult [18 - 21]. In recent times, the traffic analysis is done based on various Machine Learning (ML) techniques such as K-Means clustering, C4.5 decision tree, Support Vector Machine, Naive Bayes, etc. Among them, C4.5 is observed to have a better performance because it performs classification after segregating the input features of the dataset. C4.5 works based on flow-based statistics, without using port numbers, payload data and IP addresses, it supports encrypted form of application data. C4.5 classifies the record by either continuous or discrete attributes and also classifies the encrypted data in an appropriate manner. Thus, C4.5 is one of the most popular methods of supervised learning used for network traffic classification [6, 22, 23].

Tremendous data growth and rapid movement of vehicular users lead data offloading as one of the most feasible solutions that can be implemented using alternate technologies like small cells, WiFi, WiMAX and 3rd Generation Partnership Project (3GPP) network. Small cell networks utilize the already existing licensed spectrum which provides efficient data offloading strategy with the help of macro cell networks. Though the deployment of small cells is easy with low skilled workers, it suffers from insufficient bandwidth and the operators are also not yet ready for mass deployment [24, 25]. While offloading, there occurs certain problems like maintaining QoS, prediction of the network capacity due to dispersed and heterogeneous nature of the licensed network (2G, 3G, LTE, etc.), etc. [26, 27]. In HVN, a suitable path for offloading is selected based on the available bandwidth, loss rate and round trip time [28]. New theories are being developed to meet the QoS statistically. In WiFi offloading approach, the primary traffic gets transferred through the LTE network and WiFi acts as a supportive element [29].

Access Network Discovery and Selection Function (ANDSF), a part of Evolved Packet Core (EPC) module has been introduced which helps the user to discover nearby WiFi, based on their spatial co-ordinates for offloading the data from the LTE network to the local WiFi network, i.e., RSU in a vehicular network [30]. The position of the user and RSUs are tracked by the ANDSF module at regular interval [27]. When the user initiates the handover process, the information of the RSU location is shared by the ANDSF upon the request from the user [15, 30]. Then the user chooses the optimal RSU, which has the shortest distance from the user [30].

Selected IP Traffic Offload (SIPTO) is the method proposed in [31], which offloads the selected IP traffic to the specified network that comes in the range of user which improves the utilization of RSU. IP Flow Mobility (IFOM) allows the user for simultaneous connection of 3GPP access and non-3GPP access in which each user can manage same Packet Data Network (PDN) connection with different IP flows of different accesses. IFOM specifies solutions for seamless offloading by forwarding the best effort IP flow traffic to RSU and the remaining traffic with QoS requirements remains connected in the 3GPP (LTE) network itself [32]. With the help of IFOM and SIPTO, the user discovers the available access networks within its vicinity using ANDSF. In 3GPP release 10, this optimal RSU selection is based on the minimal distance between the user and the specific RSU.

For selecting an optimal RSU for offloading, the schemes in [13 - 15] considers approach such as user-centric, network-centric or both (hybrid). In the user-centric approach, the offloading decision is based on the parameters like Signal-to-Noise-Ratio (SNR), throughput, battery level, cost, etc. In this approach, each user makes his own decision which does not yield an optimal result as network parameters are not considered. On the other hand, in the network-centric approach, the offloading decision is based on the network parameters such as bandwidth, frequency, load-information, etc. [13]. In the hybrid approach, the network takes control of overall policy for RSU selection by considering the network conditions and the operator strategies such as revenue forecasts of voice and data services, mobile content delivery, etc. Then the overall policy is given to the vehicular user based on user-centric approach, to optimize the policy by considering the system specifications and vehicular user requirements [16]. Software-Defined Networking (SDN) acts as a promising solution which helps in dynamic optimization process due to the separation of data and control plane [17]. For intelligent decision making during data offloading, SDN controller consists of a priority manager and load balancer.

The User Equipment (UE) and Base Station (BS) information based offloading approaches try to improve the QoS but fails due to low bandwidth utilization and finally, a better QoS is achieved by using the Combined UE and BS Information (CUBI) scheme which reduces service blocking ratios and thereby enhancing aggregate throughput [13]. Vehicular-WiFi offloading techniques such as V2I and opportunistic V2V are proposed in [33 - 35] where the offloading decision is based on the offloading media, i.e., RSUs. In the cooperative downloading mechanism, RSUs play an optimal role to fetch data from the internet and distribute them to the respective vehicular users [44, 45].

For optimal RAT selection, a Q-Learning based Relative Value Iteration Algorithm (RVIA) is proposed to solve the Semi-Markov Decision Process (SMDP) problem. To sustain QoS, voice users are connected to LTE rather than the WiFi. However, for data users, the throughput offered by WiFi is higher than the LTE. When there is high load in WiFi network, the throughput may degrade and the data users need to connect to LTE networks. Policy Iteration and SMDP Q-Learning algorithms are proposed in [14] to solve the SMDP problem. In [36], the Discrete-Time Markovian Decision Process (DT-MDP) is introduced along with the Centralized Q-Learning (QC-learning) to optimize the energy consumption by Heterogeneous Cellular Network (HCN). But, it is challenging to optimize energy in HCN due to varying architectures of each device involved in the offloading scenario. This decision making and selection strategy decreases the cellular residence time and increases the offloading connection time [49].

An adaptive algorithm defines that the downloading strategy is based on the encountering time between the vehicle and the RSU. This strategy gets adjusted depending on the real situation in the vehicular network [37]. In [48], the problem of conflict resolution among multiple unmanner aerial vehicles is fomulated as a game model. SWIMMING approach is used to support seamless and efficient WiFi-based internet access in moving vehicles which consider the critical aspects of offloading data in a vehicular environment. Frequent handover in WiFi may provide inconsistent data service for high speed vehicles [38, 39]. Thus, our objective is to derive an optimal offloading algorithm for the non-safety applications vehicular network which results in efficient and intelligent RSU selection process with the help of I-ANDSF module.

III. Proposed Work

In this section, the key challenges towards the existing ANDSF module and the merits of the designed I-ANDSF module in IR-DON architecture are discussed. Then the problem statement with the system model is described. An intelligent smart Traffic Splitter algorithm is designed for classifying the user non-safety application traffic to identify the amount of traffic offloaded to local RSU network. The I-RAT selection algorithm for the selection of intelligent RSU by choosing the critical user and network centric parameters is proposed. The whole process is also demonstrated with the help of the sequence diagram in this section.

A. Key Challenges

The ANDSF comprises discovery information of available access networks that can serve a set of users in a specific geographic area. As discussed in section II, the existing ANDSF chooses an optimal RSU with the help of the geographical location of the user and the position of the RSU's. Here, an optimal RSU selection is based on the distance from the user to the respective RSU.

The fallback for the failure of existing ANDSF module comprises the following problems. Other than the function of ANDSF, the interface required to couple ANDSF and the core network need to be redesigned. The ANDSF database consists of pre-recorded information of Inter System Mobility Policy and Inter System Routing Policy for the static environment which is completely different when the devices are mobile. The communication between user and ANDSF requires additional energy which reduces the battery standby power of the user.

The proposed IR-DON architecture overcomes the above issues of the ANDSF module and achieves the following merits with the help of the designed I-ANDSF module:

- Accurate selection and prioritization of network.
- Less time delay during the switch over process from one RSU to another RSU due to degradation in QoS.
- Selection of RSU which has more resident time and serving capability.

B. System Model

Consider a HVN, which consists of one eNodeB with several RSUs in which the vehicular user transmits its traffic

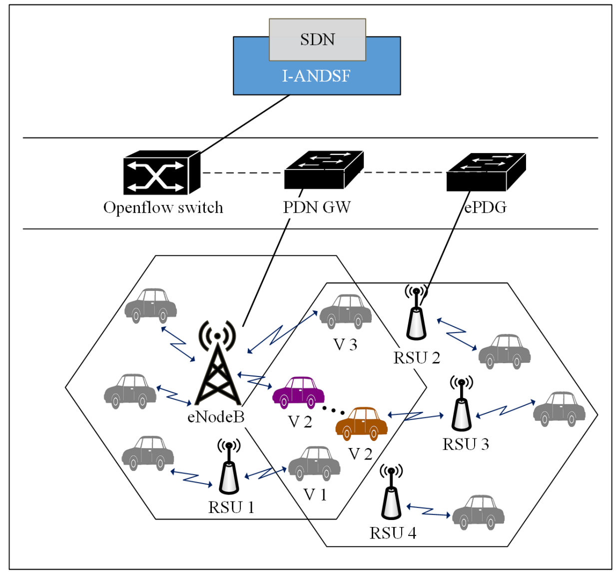

Fig. 1. System model for IR-DON under SDN controller

through cellular network or WiFi network. In HVN, RSU represents the WiFi network. Fig. 1 depicts one eNodeB centered with other RSUs. Among several vehicles, vehicles V1, V2 and V3 are considered which are in both cellular and RSU range. In the case of V1, it lies within the range of RSU1 and for V3, it gets access from the cellular network eNodeB. Consider V2 at time t0, which is in range of the cellular network, so it gets connected to the eNodeB at time t0. Then at time t1, due to mobility, V2 moves out of range of the cellular network, which now needs to choose the RSU that provides efficient QoS. For V2, the existing ANDSF selects the RSU with minimal distance. i.e., in this case, it selects RSU4. But the proposed IR-DON architecture consists of I-ANDSF module with SDN controller which is designed to choose an optimal RSU among the available ones using the reward computed by the Q-Learning module. Here an optimal RSU selection depends upon both network and user-centric parameters. Based on the user non-safety application traffic, the offloading type is chosen, and then a network is selected using the reward values calculated for both cellular and local RSU. By calculating the reward values of all available RSUs and the eNodeB, V2 selects the RSU with maximal reward value, i.e., in this case, it selects RSU3.

C. Intelligent Reward based Data Offloading Model

In HVN environment, the user can come up with time sensitive critical and delay tolerant types of non-safety application. The application service request received by the cellular network is sent to the SDN which acts as a centralized controller. Here, the SDN controller helps to classify the traffic as safety and non-safety with the help of I-ANDSF module and based on the characteristics of the application such as packet size, sensitivity of the application, round trip time, etc. The list of frequently used notations are enlisted in Table I.

1) Smart Traffic Classification: As discussed in section II, ML algorithms can overcome the drawbacks of both port

TABLE I
FREQUENTLY USED NOTATIONS

Notation	*Description*
σ	Packet Generation Rate
λ	User Arrival Rate
μ	User Service Rate
d_i	Required Data Rate
L_i	Packet Loss Bound Ratio
P_i	Primitive Index
S_i	Number of Successful Transmissions
P_k	Position of the Vehicular User
T_i	Traffic
π^*	Optimal Policy
V^*	Maximal Expected Cumulative Reward
δ	Discount Rate
CH_L	Channel Load
PS	Average Packet Size
A	Set of Actions
B	Number of eNodeBs
c	Number of servers
J	Additional Reward Factor
N	Number of Users
R	Number of RSUs
R_RSU	Reward of RSU
R_C	Reward of Cellular Network
S	Set of States

based and payload based techniques. ML based application traffic classification does not depend on the traffic statistics like window size, round trip time, packet length, etc. In the proposed IR-DON architecture, the user requested non-safety application traffic can be classified based on the robust C4.5 decision tree algorithm. In our system, users are ‘vehicles’. So, we do not distinguish the terms users and vehicles.

After the traffic classification is performed for each user application, safety traffic can be offloaded using opportunistic offloading and non-safety traffic can be offloaded using delayed offloading.

For each user application in HVN, the functions of SIPTO can be activated during user mobility and traffic aggregation process. For effective functioning of SIPTO, the offloaded amount of data traffic for each user application and RSU's usage are calculated. The calculation of the amount of traffic to be offloaded to the local RSU depends upon the RSU's supportable data rate and the data rate needed for each user application. For each user application request, QoS satisfied and unsatisfied applications are classified and based on this, primitive index (P_i) value is given for each application. Our proposed Traffic Splitter algorithm then ranks the user application based on the application's P_i value.

Algorithm 1 describes the proposed Traffic Splitter algorithm which consists of 5 phases, viz. Initialization phase, Calculation phase, Splitting phase, Comparison phase and Ranking phase.

In Initialization phase, the values of Traffic offloaded to Cellular Network (T_{CN}), Traffic offloaded to Local RSU (T_{LR}) and Traffic existing in core Cellular Network Alone (T_{CN_ALONE}) are initialized to zero.

In Calculation phase, the values of Data Rate Supportable (DRS) for the local RSU and the Effective Data Rate (EDR) needed for the user application are calculated.

$$DRS_{LR} = \sigma_{Cr\_LR} \times N_{LR} \times PS_{LR} \tag{1}$$

where σ_{Cr_LR}, N_{LR} and PS_{LR} denotes the user's critical packet generation rate, total number of users and average packet size in the local RSU respectively. EDR of each user application which satisfies QoS can be calculated as follows,

$$EDR_i = d_i \times s_i \times (1 - L_i) \tag{2}$$

where d_i denotes the required data rate of each application considering delay bound, peak data rate, burst size and mean data rate, s_i and L_i implies number of successful transmissions to send a packet and packet loss bound ratio. The value of d_i and s_i depends upon the user application.

In Splitting phase, the User Application $UA[i]$ traffic T_i can be classified into offloaded traffic to local RSU (T_{OL}) and core cellular network traffic alone (T_{CN_ALONE}). If $UA[i]$ contains core cellular network traffic alone, then core Cellular Network traffic alone of application i ($T_{i\_CN\_ALONE}$) can be classified into total core cellular network traffic (T_{CN_ALONE}) and offloaded traffic of application i (T_{i_OL}). This T_{i_OL} is then offloaded to local RSU.

In Comparison phase, the EDR of each application is compared with DRS value of the local RSU. If the value of EDR of each application is less than the DRS value of the local RSU, then the P_i value can be set for each application based on the Criteria based Order of Preference (COP). COP works by sorting the application based on its usage, QoS requirement and type of the application like video, audio, files, browsing, messaging, etc.

In Ranking phase, each application is ranked based on the P_i value. If the value of EDR exceeds the value of DRS then the value of P_i turns to zero. The highest P_i value of the application's traffic is classified into Local RSU traffic (T_{LR}) and other traffic is classified into core Cellular Network traffic (T_{CN}). Here T_{LR} is offloaded into local RSU, T_{CN_ALONE} and T_{CN} go to the core Cellular Network.

2) Critical Parameter Selection to Trigger Offloading: The proposed IR-DON architecture consists of evolved Packet Data Gateway (ePDG) module for secure communication between vehicular user and the core cellular network (3GPP access) over non-3GPP access like WiFi, Femto, etc. With the help of the interconnecting point known as Packet Data Network Gateway (PDN GW), the non-3GPP access WiFi can have secure access to connect with the core cellular network. The Open Flow (OF) controller interacts with the I-ANDSF module to find an intelligent RAT for the vehicular user. After splitting the amount of traffic in Traffic Splitter algorithm, ranking of user non-safety application traffic is performed based on the application's P_i value. After ranking phase, the amount of traffic to be offloaded to local RSU and the amount of traffic natively used by the cellular network are identified. For each of this offloaded non-safety application traffic, the user is be provided with a set of five optimal RAT's based on the reward value of each RAT. This optimal network selection for offloading is used to increase the overall throughput of the system.

Algorithm 1: Traffic Splitter

Input: User application service request UA[i]
Output: Amount of traffic offloaded to local RSU and core Cellular Network

Initialization:
$T_{CN\_Alone} = 0$, $T_{LR} = 0$, $T_{CN} = 0$
Number of iterations, i $\leftarrow$ 1
Derive the value of Data Rate Supportable (DSR) for the Local RSU
$DRS_{LR} = \sigma_{Cr\_LR} \times N_{LR} \times PS_{LR}$
for *i = 1.. n in UA[i]* **do**
  Derive each application's Effective Data Rate
  $EDR_i = d_i \times s_i \times (1 - L_i)$
end for
for *i = 1.. n in UA[i]* **do**
  if *UA[i] contains core network traffic alone* **then**
    $T_{CN\_Alone} \leftarrow T_{CN\_Alone} + T_{i\_CN\_Alone}$
    $T_{i\_OL} \leftarrow T_i - T_{i\_CN\_Alone}$
  else
    $T_{i\_OL} \leftarrow T_i$
  end if
end for
for *i = 1.. n in UA[i]* **do**
  if $EDR_i < DRS_{LR}$ **then**
    Calculate Primitive Index P_i by COP
  else
    $P_i = 0$
  end if
end for
Rank the UA[i] depending on P_i
for *i = 1.. n in UA[i]* **do**
  if *P_i of the application i in UA[i] is the maximum* **then**
    $T_{LR} \leftarrow T_{LR} + T_{i\_OL}$
  else
    $T_{CN} \leftarrow T_{CN} + T_{i\_OL}$
  end if
end for
T_{LR} is offloaded to Local RSU, T_{CN} and T_{CN_ALONE} goes to the core Cellular Network

The combined user-centric and network-centric approach in the proposed IR-DON architecture is shown in Fig. 2, where offloading is done based on Combined User and Network Information (CUNI) parameters such as bandwidth, load information, etc. on the network side and battery power, Signal-to-Interference-plus-Noise-Ratio (SINR), etc. on the user side.

The I-RAT selection problem is formulated as Markov Decision Process (MDP) problem. Among the various methods of Reinforcement Learning (RL), Q-Learning is one of the efficient methods to find an optimal policy based on the reward that the users choose in the dynamic network environment. In Fig. 3, the user interacts with the overall network which is

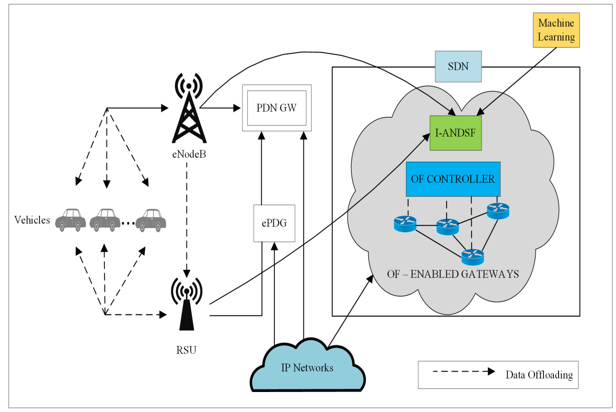

Fig. 2. Architecture Diagram of IR-DON

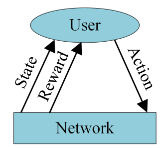

Fig. 3. User Network Interaction Diagram

completely different from the user's environment. For each step, the user receives an input from the network that is represented as a state. In that state, the user selects an optimal action with the help of a SDN controller. This is a sequential process and it results in reward r and transfer of current state s to the next state s'. Here the interaction between the user and the SDN controller happens with the help of I-ANDSF module.

The elements of the Q-Learning algorithm as follows:

State: s' ϵ S

Here the state represents the positions of the vehicular user as $\{P_k$ at time t, k ϵ $\{1, 2, .., N\}$ $\}$ where N is the number of users.

Action: a' ϵ A(s)

The location of the RSU detected by the vehicular user as $\{Loc\_RSU_k$ at time t, k ϵ $\{1, 2, .., R\}$ represents the set of actions, i.e., the set of RSUs detected by the user. Here R denotes the number of RSUs. The user selects the action 'a' at time 't' as { 0,1,...R }. If the user selects a' = 0, then the user remains to connect with the existing eNodeB connection. If the user select a' = { 1,...R } then the user selects the particular RSU at time t and gets connected to it.

Agent: The vehicular user follows a feasible path with positions P1, P2, P3 and P4.

Reward: For reward calculation, reward values of RSU, cellular networks and its threshold are considered. Let R_RSU and R_C be the reward values of RSU and cellular network respectively. After computing these two values the user selects the maximal reward value and takes the decision accordingly.

The user's main goal is to maximize the immediate reward. So, it finds an optimal policy to increase the reward in a short time with lesser number of iterations. Here the next state of the network does not depend on the previous state and the actions get executed based on that particular state. This property refers to Markov Process and it can be stated as MDP.

MDP consists of

1. A set of possible states S and its action A
2. The transition Probability is given by,

$$P(s,a,s') = P\left\{s_{t+1} = s' | s_t = s, a_t = a\right\} \tag{3}$$

3. The immediate reward is given by

$$R(s,a,s') = E\{r_{t+1} | s_t = s, a_t = a, s_{t+1} = s'\}^2 \tag{4}$$

Here E denotes Expected immediate reward.

For each state s, $a \, \epsilon \, A(s)$ represents an action in a particular state s in which $s' \;\; \epsilon \; S$.

For each time step t, the agent receives a reward for an optimal action from the network and then sum up the discounted reward that the user receives in the future. Thus, the optimal policy to find the reward is denoted by π^* and is given by,

$$\pi^* : A \leftarrow S \tag{5}$$

The optimal policy depends on the action performed in the respective states. Then the discounted cumulative reward $V(s,a)$ for this optimal policy π^* is given by,

$$V(s,a) = R(s,a,s') + \delta \Sigma_{s' \varepsilon S} P\left\{s_{t+1} = s' | s_t = s, a_t = a\right\} V(s',a) \tag{6}$$

In Equation (6), R(s,a,s') belongs to the immediate reward, $P\left\{s_{t+1} = s' | s_t = s, a_t = a\right\}$ be the transition probability and δ is the discount rate and its range is from 0 to 1.
Using Bellman's theory [40], the maximal discounted cumulative reward is given by,

$$V^*(s,a) = max\{R(s,a,s') + \delta \Sigma_{s' \varepsilon S} P\{s_{t+1} = s' | s_t = s, a_t = a\} V(s',a)\} \tag{7}$$

V^*(s,a) is the maximal expected cumulative reward when the user follows an optimal selection policy π^*. Then by using this reward function, an optimal policy π^* is derived,

$$\pi^*(s,a) = arg \quad max_{a \varepsilon A(s)} V(s',a) \tag{8}$$

From this, an optimal action-value function Q^π(s,a) is calculated as

$$Q^\pi(s,a) = R(s,a,s') + \delta \Sigma_{s' \varepsilon S} P\left\{s_{t+1} = s' | s_t = s, a_t = a\right\} V^\pi(s',a) \tag{9}$$

This Q-value can be used to find an optimal selection policy. Q-Learning is the method to select an optimal action without any explicit model i.e., predefined model. So, this method is called as model free method of RL techniques. The I-RAT selection is described in Algorithm 2.

The vehicular user interacts with the network (VANET) environment and it receives a state from the network as input. At time t_0, depending on the state s the user decides to perform an action a i.e., an optimal RAT selection for that particular position. By choosing an optimal RAT from the set $\{1, ...R\}$ as action a, the user needs to move to the next state s'. For each next state s', the user receives an immediate reward R. The main goal of the user is to maximize the cumulative reward. The best policy selection is based on the vehicular user's movement and interaction with the environment.

The reward for cellular network R_C can be calculated using the received SINR value from the eNodeB to the vehicular user.

$$R\_C = SINR\_C \tag{10}$$

$SINR\_C$ be the Signal-to-Interference-plus-Noise-Ratio for cellular network.

The reward for RSU R_RSU needs to be appropriately calculated to make the vehicular user connect to alternative RSU which is near to the user without any loss in QoS. So, the reward value R_RSU not only depends on received SINR but also on RSU's load value, additional reward factor to provide successful offloading and the delay during handover.

$$R\_RSU = \frac{SINR\_RSU \times J \times 255}{L \times T \times D\_HO} \tag{11}$$

Here $SINR\_RSU$ be the Signal-to-Interference-plus-Noise-Ratio for RSU, J be the additional reward factor which increases as the distance between the user and the eNodeB decreases with time t.

The Channel Load value CH_L can be calculated as,

$$CH\_L = \frac{channel\ busy\ value}{T} \times 255 \tag{12}$$

where T be the time duration for network connection. This load value represents the percentage of time that the RSU is busy (scaled linearly by 255 which denotes 100%).

Algorithm 2: Intelligent RAT (I-RAT) selection

Input: Offloaded non-safety application traffic
Output: Optimal RAT for the user to establish connection

```
Initialization:
Number of iterations, i ← 1
Set initial value of Q-Value as Q(s,a) ← 0
∀ s ϵ s' and ∀ a ϵ A for each user u do
    Initialize the user's current state s
    for each user position s do
        Choose action (Optimal RAT selection) a from s
          using the policy π*
        Observe the reward r for the current state s
        Go to next state (user position) s'
        Update Q(s,a) from Equation Q_t(s,a)
        Update s ← s'and i ← i + 1
    end for
end for
Determine an optimal set of five RSU's by observing
  RATs reward values.
```

D_HO be the Delay in Handover process which is also considered as a part of reward value for RSU. By considering the delay value during the handover process, we try to reduce the service disconnection probabilities, which guarantee the

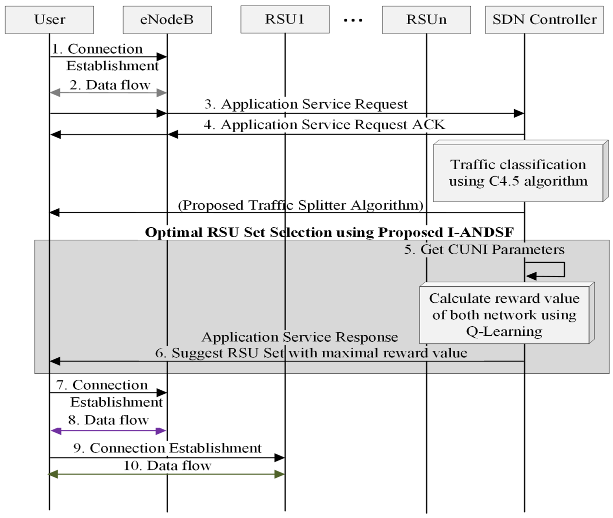

Fig. 4. Sequence Diagram for Data Flow based on IR-DON

QoS. By substituting Equation (12) in Equation (11), the value of R_RSU becomes,

$$R\_RSU = \frac{SINR\_RSU \times J}{channel\, busy\, value \times D\_HO} \tag{13}$$

Here R_RSU is directly proportional to the received SINR value. So, if the SINR value increases then there is a possibility that the user will switch over to the local RSU.

For each user's position in the network, the vehicular user needs to follow these steps:

1) Interact with the environment and observes the current state s
2) For each state $s' \epsilon$ S, select the action $a \epsilon A(s)$
3) Receive the immediate reward $R(s, a, s')$ and tries to maximize the reward value to select an optimal policy $\pi *$.
4) These steps can be repeated until the Q-Learning algorithm reaches its convergence value.

The Q-value update depends on the current state s, action performed a, next new state s' and the immediate reward value $R(s, a, s')$. For each iteration the Q-value can be updated as follows:

$$Q_t(s,a) = Q_{t-1}(s,a) + \beta[R_t(s,a,s') + \delta max_{a\varepsilon A(s)} Q_{t-1}(s',a') - Q_{t-1}(s,a)] \tag{14}$$

β is the learning rate and it varies from 0 to 1. Q-value varies with respect to the previous iterations.

Fig. 4 shows the entire sequential process of the proposed IR-DON. Any user that established its connection with LTE network with the help of secured authentication can also connect to local RSU when it comes under RSU coverage with maximum QoS gain. Here, the SDN controller classifies the user application service request into critical time sensitive and delay tolerant applications using C4.5 decision tree algorithm. Here C4.5 classifies each user application service request from the top (root) then pass recursively into the lower categories (trees) until it classifies them into either time sensitive or delay tolerant ones (leaf node). The amount of traffic offloaded to local RSU can be determined using Traffic Splitter algorithm. Based on the CUNI parameters, the reward values of each RAT are calculated then the user chooses the RSU with maximal reward value. For this efficient RSU selection, I-ANDSF plays an important role in I-RAT selection algorithm. After selecting the optimal RSU, the connection establishment between user and the respective RSU takes place and the data gets transmitted seamlessly.

IV. Mathematical Analysis

In this section, HVN environment is considered as Multiple Server Infinite Length Queueing model. The eNodeB and the RSU are considered as two types of servers and the queue consists of the number of users connected to these networks. The length of the queue depends on number of users connected.

The arrival rate of the user follows poisson distribution with probability $\lambda/hour$ and the user gets serviced by exponential distribution with probability $\mu/hour$. The two types of RAT's such as eNodeB and local RSU are denoted as B and R respectively. Total number of servers is denoted by c and can be calculated as,

$$c = B + R \tag{15}$$

The service rate for serving n group of users by c servers is given by μc. Probability of n group of users connected with any one of the RAT at time t can be derived as follows:

$$P_n = \frac{\lambda^n}{\mu^n c! c^{n-c}} P_0 \qquad if\ n \geq c \tag{16}$$

$$P_n = \frac{\lambda^n}{\mu^n n!} P_0 \qquad if\ n < c \tag{17}$$

Equation (16) and (17) are the probability values of n group of users in a cell when the number of RATs is lesser than or equal to the n group of users and when the number of RATs is greater than the available n group of users respectively.

Probability when there is no user in the network P_0 can be derived as,

$$P_0 = \frac{1}{\sum_0^{c-1}} \frac{\lambda^n}{\mu^n n!} + \frac{\lambda^c}{\mu^c c! [\frac{1}{1-\frac{\lambda}{\mu c}}]} \tag{18}$$

The length of the queue for this network L_N_q can be calculated as,

$$L\_N_q = \frac{\lambda^{c+1}}{\mu^{c+1} c!} \frac{c}{(c - \frac{\lambda}{\mu})^2} P_0 \tag{19}$$

The length of the queue including the user to be served can be calculated using Equation (19) as,

$$L\_N_s = L\_N_q + \frac{\lambda}{\mu} \tag{20}$$

The waiting time of the user to get served by the network and the waiting time of the user spent in the queue are calculated as,

$$W_q = \frac{L\_N_q}{\lambda} \tag{21}$$

$$W_s = \frac{L\_N_s}{\lambda} \tag{22}$$

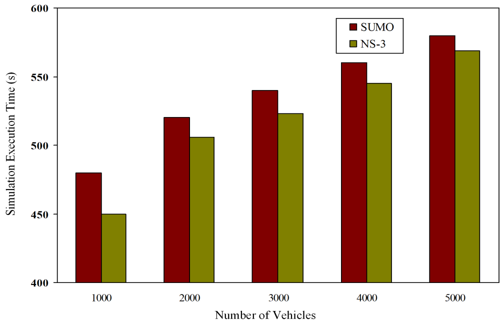

Fig. 5. Simulation Time Vs No. of Vehicles for different simulations

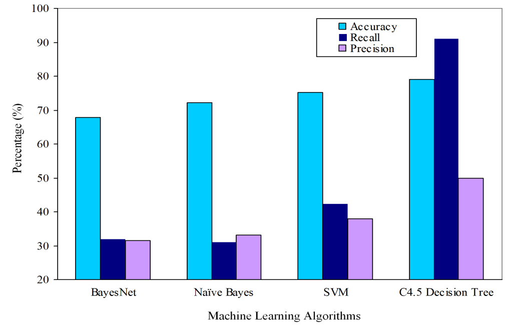

Fig. 6. Traffic Classification Accuracy of Different ML Algorithms

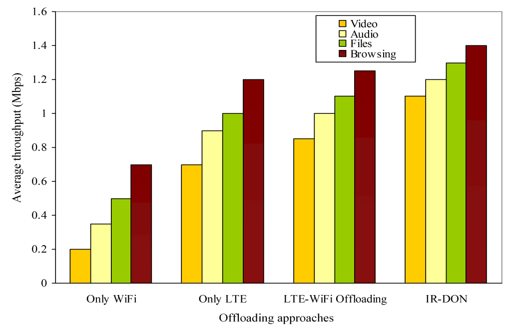

Fig. 7. Throughput of Users on Different Offloading Strategies

The expected utility function for the user is given by,

$$E[u(x)] = \sum_{j=0}^{R} P_j u_j \tag{23}$$

The value of P_i depends upon the server chosen by the user either cellular network or local RSU. The utility values (u_j) can be represented as $\{u_0,...u_R\}$. u_0 represents the cellular network utility and $\{u_1,...u_R\}$ represent the utility values of the respective RSUs.

$$E[u(x)] = P_0 u_0 + \sum_{j=1}^{R} P_j u_j \tag{24}$$

By substituting the Equations (16), (17) and (18) in Equation (24), the expected utility function becomes,

$$E[u(x)] = \frac{1}{\sum_0^{c-1} \frac{\lambda^n}{\mu^n n!} + \frac{\lambda^c}{\mu^c c!}[\frac{1}{1-\frac{\lambda}{\mu c}}]} \mu_0 + \sum_{i=1}^{R} \frac{\lambda^i}{\mu^i c! c^{i-c}} P_0 u_i \quad if\ i \geq c \tag{25}$$

$$E[u(x)] = \frac{1}{\sum_0^{c-1} \frac{\lambda^n}{\mu^n n!} + \frac{\lambda^c}{\mu^c c!}[\frac{1}{1-\frac{\lambda}{\mu c}}]} \mu_0 + \sum_{i=1}^{R} \frac{\lambda^n}{\mu^n n!} P_0 u_i \quad if\ i < c \tag{26}$$

The utility values are calculated based on the load of the server and the priority value of the application set by the user. Among the utility values of the cellular network and local RSU, the user selects the network with maximum utility value.

The utility value from the cellular network and RSU are denoted by $U_0(l,p,t)$ and $U_i(l,p,t)$ where l, p and t are the load information of the network, priority of the user application and residence time of the network connection.

$$u_j = max\{U_0(l,p,t), U_i(l,p,t)\} \tag{27}$$

Using these probability and utility values, the overall dynamic nature of the HVN environment is identified and the appropriate RAT is selected. By utilizing these equations in MATLAB environment, the respective waiting time and probability graphs are devised in the following performance analysis section.

V. Performance Analysis

The proposed IR-DON architecture with I-ANDSF module is implemented using NS-3 and Simulation of Urban Mobility (SUMO) simulators. For realistic implementation of VANET environment, we used both Network (NS3) and Traffic (SUMO) simulators. The implementation process comprises two steps. Firstly, SUMO generates a trace file of the entire simulation of transportation environment. Secondly, with the help of the generated trace file, NS3 simulates wireless network communication among vehicles and RSUs. Fig. 5 shows the average simulation time taken for both NS3 and SUMO when there is an increase in number of vehicles in the VANET environment. Traffic Control Interface (TraCI) is used to couple NS3 and SUMO simulators. With the help of the simulated architecture, TraCI helps in monitoring the mobility of each and every vehicle dynamically. Simulation parameters are shown in Table II. In the simulation, the Q-Learning python module extracts the necessary information for reward calculation such as SINR, distance from the vehicular user to the respective RAT, handover delay, channel load value, etc. Using the output from the python module, an optimal set of five RSUs is identified. Among the available RSUs in the set, the user establishes its connection with the maximal reward value RSU; if the user experiences any congestion or degradation in QoS, then it automatically switches its connection from the maximal reward value RSU to second maximal one. From the analysis in Fig. 6, it is clear that the accuracy, precision and recall of C4.5 are higher compared to other machine learning algorithms [7, 23, 47]. So, for traffic classification, we use the already existing C4.5 decision tree

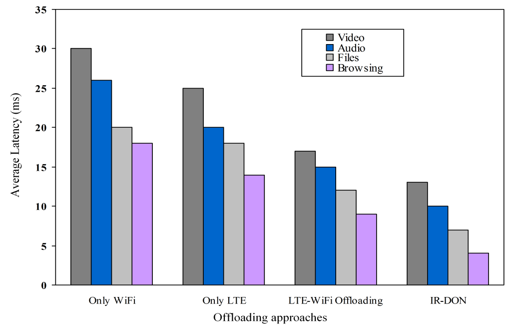

Fig. 8. Latency of Users on Different Offloading Strategies

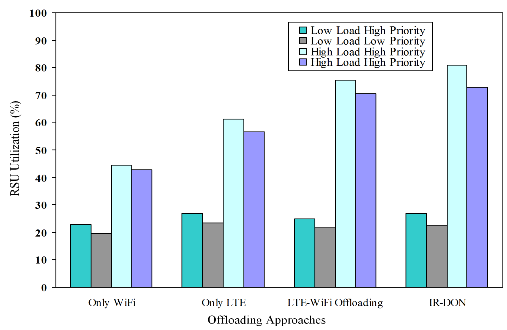

Fig. 9. RSU Utilization on Different Offloading Strategies

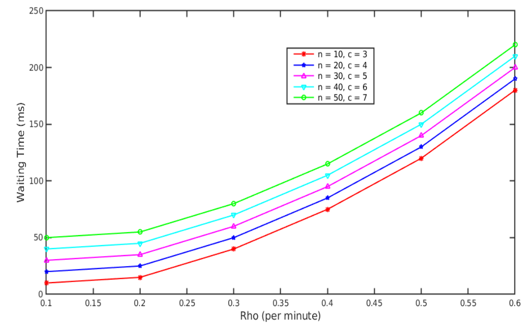

Fig. 10. Waiting Time vs Rho (arrival rate/service rate)

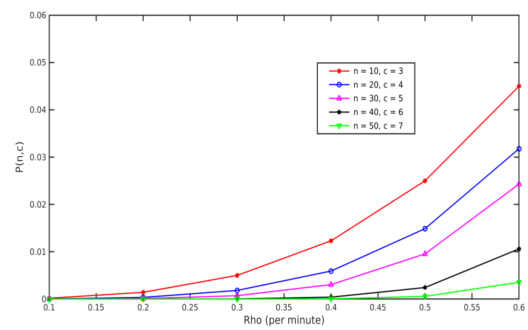

Fig. 11. Effect of Rho (arrival rate/service rate) on P(n,c)

algorithm to split critical safety and delay sensitive non-safety applications.

TABLE II
SIMULATION PARAMETERS

Parameter	***Value***
LTE Scheduler	RrFfMacScheduler
Mobility (eNB, RSU)	ConstantPositionMobilityModel
Mobility (Vehicle)	WayPointMobilityModel
Mobility (UE)	RandomWalk2dMobilityModel
RSU Channel	YansWiFiChannel
RSU Rate Control	AARF Rate Control
Path Loss Model (LTE)	FrisPropogationLossModel
Path Loss Model (RSU)	LogDistancePropogationLossModel
Transmit Power (eNB)	42 dBm
Transmit Power (RSU)	25 dBm
Noise Figure (eNB)	4 dB
Noise Figure (RSU)	2.5 dB
Carrier Frequency	2.16 GHz
System Bandwidth	6 MHz
Number of Channels	25
Inter eNB distance	500 m
Inter Vehicular distance	25 m

Fig. 7 and Fig. 8 show the average throughput and latency values of users when connecting the user with WiFi, LTE, both LTE and WiFi [13, 41] and the proposed IR-DON architecture. When users with different non-safety application traffic need a network connection, they will automatically get connected to any one of the network based on their application type. Here connecting users with various offloading approaches for a different type of applications such as video, audio, messaging, browsing, etc. are considered. From this analysis, we arrive at the conclusion that the proposed IR-DON outperforms the existing approaches in terms of increase in average throughput with a reduced delay for connection establishment.

Fig. 9 shows the RSU Utilization in percentage (%) for various offloading approaches [14] including the proposed IR-DON method where there is high and low load in the network with respect to priority of QoS. In the proposed IR-DON architecture, maximum RSUs are utilized by the user and almost all users get dedicated QoS connection.

Fig. 10 shows the effect of Rho (arrival rate/ service rate) on waiting time of the user to get served by the network from Equation (22). Here we analyze this waiting time by increasing the number of users n and the number of RATs c. Thus, the waiting time is an increasing function with increase in n and c values. Fig. 11 describes the effect of $P(n, c)$, i.e., the probability of the user connected with any one of the RAT at time t with respect to Rho (arrival rate/ service rate) from Equations (16) and (17). With increase in n and c values the probability of the user getting a connection is decreased. Thus we conclude that, when there is an increase in number of users and number of RATs, then $P(n, c)$ becomes a decreasing function.

VI. CONCLUSION

In this paper, the issue of RAT selection in congested HVN is addressed with the proposed IR-DON architecture. After traffic classification by C4.5 algorithm, the user decision making strategy depends on the reward values calculated for each respective RAT. This reward calculation with CUNI parameters helps the I-RAT selection algorithm in which an efficient model free reinforcement learning technique called Q-Learning with integrated I-ANDSF module is designed. In this algorithm, the user builds their Q-table by learning the local environment and adapts to the HVN environment by taking optimal decisions at each position. Q-Learning algorithm works until the convergence value is reached. After getting the convergence value, the user gets ready to choose an optimal network at that particular state, i.e., position. Here the RSU residence time is increased by following the efficient reward based I-RAT selection algorithm. Thereby, compared to existing offloading approaches, the proposed IR-DON architecture improves the overall throughput of the system by 17% with a reduced delay of 15%. Thus, IR-DON provides guaranteed QoS. The results show that IR-DON gives improved results even with the wide range of users. The future work is to optimize this strategy of IR-DON with a high load in WiFi and LTE networks and to achieve even better QoS.

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Gunasekaran Raja (M'08, SM'17) is working as a Professor and Head in the Department of Computer Technology at Anna University, Chennai and Principal Investigator of NGNLab. He received his Ph.D. in 2010 under the Faculty of Information and Communication Engineering from Anna University, Chennai. He was a Post-Doctoral Fellow at University of California, Davis, USA. His current research interest include 5G Networks, Internet of Vehicles, IoT, Wireless Security, Mobile Database, Machine Learning, UAV Communication, Hybrid LiFi/WiFi and Data Offloading. He was a recipient of Young Engineer Award from Institution of Engineers India in 2009, FastTrack grant for Young Scientist from Department of Science and Technology in 2011, Professional Achievement Award for the year 2017 from IEEE Madras Section and Visvesvaraya Young Faculty Research Fellowship from MeitY, Govt. of India in 2019.

Aishwarya Ganapathisubramaniyan pursued her Bachelor of Computer Science and Engineering from Anna University, Chennai in 2018. Currently, she is working as an Application Developer at Citicorp Services Pvt Ltd. She was a recipient of Meritorious Student Award and Delhi MIT Alumni Association Prize from Anna University, Chennai in 2017. Her areas of interests include Vehicular Networks, Data Offloading, Machine Learning, SDN, UAV Communication, Cryptography and Network Security.

Sudha Anbalagan is currently working as an Assistant Professor in the Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur, India. She received the B.Tech degree in Information Technology from Amrita university, Coimbatore in 2007, M.E degree in Computer Science and Engineering from Anna University, Chennai in 2013. She received her Ph.D in Department of Information Technology from Anna University, MIT Campus. She was also a visiting research fellow for a period of 9 months with the Department of Computer Science, University of California at Davis, USA. Her research interest includes 5G, LTE-A, Software Defined Networking, Data Offloading and Network Security.

Sheeba Backia Mary Baskaran is currently working as a Senior Researcher and 3GPP SA2 delegate with Huawei Technologies, Sweden. Previously she worked with NEC India Pvt. Ltd. as a Research Engineer and 3GPP SA3 delegate. She received her Ph.D. in Information and Communication Engineering from Anna University, Chennai in 2017. She was a member of NGNLabs Anna University and was a recipient of Maulana Azad National Fellowship from 2013-2016. She has 4 years of experience in Research and Development of mobile communication networks security aspects and 2 years plus experience in 3GPP 5G system and security standardization. She previously carried out her research in Security Solutions for 5G, URLLC, Public Safety network and Common API Framework. Her research interest includes 5G URLLC, Vertical Services, eNA, Public Safety, IoT, Industry 4.0, and MAC layer protocol design. She has also contributed to Regional standardization body-Global ICT Standardization Forum for India (GISFI).

Kathiroli Raja is working as an Assistant Professor in the Department of Computer Technology, Anna University, Chennai, India. She received her Ph.D. from Anna University in the year 2016. She received her M.E. degree in the field of Computer Science and Engineering from Anna University in 2008. Her area of interest includes wireless networks, Adhoc Networks, Data Mining and Machine learning.

Ali Kashif Bashir (M'15, SM'16) is working as an Associate Professor in Department of Computing and Mathematics, Manchester Metropolitan University, UK. He received his Ph.D. degree in computer science and engineering from Korea University, South Korea. In the past, he held appointments with Osaka University, Japan; Nara National College of Technology, Japan; the National Fusion Research Institute, South Korea; Southern Power Company Ltd., South Korea, and the Seoul Metropolitan Government, South Korea. He is leading several research projects and supervising/co-supervising several undergraduate and graduate (MS and PhD) students. His research interests include cloud computing, NFV/SDN, network virtualization, network security, IoT, computer networks, RFID, sensor networks, wireless networks, and distributed computing. He has chaired several conference sessions and gave several invited and keynote talks. He is serving as the Editor-in-chief of the IEEE INTERNET TECHNOLOGY POLICY NEWSLETTER and the IEEE FUTURE DIRECTIONS NEWSLETTER.