Res6Edge: An Edge-AI Enabled Resource Sharing Scheme for C-V2X Communications towards 6G

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***Abstract*—The paper proposes a sixth-generation (6G)-enabled cellular vehicle-to-anything (C-V2X)-based scheme, *Res6Edge*, that supports high-data ingestion rate through artificial intelligence (AI) models at edge nodes, or Edge-AI. Through Edge-AI in 6G supported C-V2X, we address the research gaps of earlier schemes based on fifth-generation (5G) resource orchestration. 6G improves decision analytics and real-time resource sharing among C-V2X ecosystems. The scheme operates in three phases. In the first phase, a layered network model is proposed for V2X communication based on 6G-aggregator and core units. Then, based on the proposed stack, in the second phase, 6G resource allocation is proposed through macro base station (MBS) units. MBS ensures channel gain and reduces energy loss dissipation. Finally, in the third phase, an intelligent edge-AI scheme is formulated based on deep-reinforcement learning (DRL) to support responsive edge-cache and improved learning. The proposed scheme is compared to 5G baseline services in terms of parameters like- throughput, latency, and DRL scheme is compared to random allocation approaches. Through simulations, *Res6Edge* obtains a V2X user throughput of 43.24 Mbps, compared to 0.7 Mbps for 4×10^8 connected ACV sensors. The reduced latency is ≈ 13.84 times of 5G. DRL learning algorithm achieves a satisfaction probability of 0.5 for 500 vehicles, compared to 0.35 using conventional schemes. The obtained results indicate the viability of the proposed scheme.**

***Index Terms*—6G, Resource sharing, Resource allocations, Edge-AI, Vehicle-to-anything.**

I. Introduction

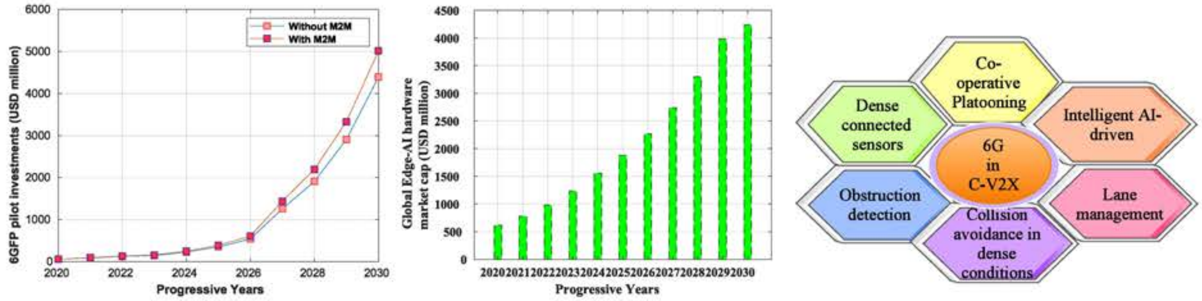
Modern cellular V2X (C-V2X) communications have emerged as a key enabler for autonomous connected vehicles (ACVs). C-V2X ensures automated, responsive, safe, and effective driving through sensor-driven integration, and communicates with peer ACVs, pedestrians, and road side infrastructure (RSI) through vehicle-to-vehicle (V2V), vehicle-to-pedestrian (V2P), and vehicle-to-infrastructure (V2I) link respectively. In C-V2X communication, the 5G band leverages dense sensor interactions in communicating heterogeneous networks (HetNets). It also envisions a responsive, low-latency, and resilient communication infrastructure to offload/download traffic from V2X links, through services like enhanced mobile broadband (eMBB) to provide high throughput to live streaming networks and ultra-responsive low latency communication (URLLC) for responsiveness.

C-V2X is a highly resource-intensive network that can drain sensor batteries too early and makes the network lifetime short. Moreover, the end-user communication latency among peer-ACVs is high (i.e., $> 10ms$) in LTE-based networks. To cope up with the stringent communication requirements in C-V2X communications, researchers explored the possibility of integration of 5G-based cellular schemes. However, the data is exchanged via public open channels, i.e., the Internet, which attracts a malicious user to launch network-based attacks that can cause network jamming and reduces network reliability [4].

The aforementioned issues related to C-V2X communication can be mitigated with artificial intelligence (AI) and mobile edge computing (MEC)-enabled intelligent traffic accident detection systems [5]. 5G integrated MEC leverages high data rate, high availability, real-time interaction, and processing for better performance. MEC adopts a decentralized model that makes computing near the device rather than a cloud to reduce latency and increase security [6]. Because of small-scale servers (mobile edge servers), the user mobility can be affected and causes many issues like service disruption, mobile connectivity, and network issues (when we move from location to another). Also, in 5G there were delays (end-to-end delay) and security issues which are important factors for user experiences [7].

Some of the above mentioned limitations of 5G mentioned above can be solved by 6G networks, which offers mobile broadband reliable low latency communication (MBRLLC) that improves the performance of C-V2X communications. These wireless-access networks have multiple base stations (BSs) or access points (AP) to provide uninterrupted network services. To provide services to million smart devices within a small geographical location, the APs/BSs are densely located in the 6G network. 6G is envisioned to offer last-mile connectivity to legacy networks at higher frequency terahertz (THz) bands, virtual physical and media-access channels, sub-mmwave channels, extremely low-latency, and high availability [1]. In C-V2X based ecosystems, it allows dense connectivity among ACVs and allows responsive resource sharing. A comparative analysis of the 6G flagship projects (6GFP) and estimated market cap until 2030 is presented in Fig. 1a. It is estimated that by 2030 around 5016 million US dollars (USD) would be invested for massive machine-to-machine (M2M) communications in C-V2X, and ≈ 4394 USD would be invested for non-M2M communications. To offer responsive services, the 6G program orchestrates a responsive edge-AI-based mechanism that is intelligent and pervasive. Thus, 5G-supported AI-enabled MEC services are present in 6G, with an intelligently layered stack.

Edge-AI techniques with powerful abilities can be employed in the 6G networks to intelligently carry out performance optimization, knowledge learning, and complicated decision



(a) 6GFP pilot investments market caps by 2030 worldwide [1]
(b) Global Edge-AI hardware and device market cap by 2030 [2]
(c) Benefits of 6G integration in C-V2X ecosystems [3]

Fig. 1: Global market 6G flagship pilot projects by 2030 and observed impact of 6G in C-V2X communications

making. Edge-AI and 6G aims are expected to bring a completely wireless and automated experience. Loven *et al.* [2] estimated the global edge-AI hardware requirements to support network devices at a responsive edge to stand at the market cap to reach a staggering 4239.62 USD by 2030, with a compounded annual growth rate estimated at 20.66%. The comparative market cap is presented in Fig. 1b. AI can increase efficiency and reduce the processing delay of the communication steps for better performance.

Edge-AI services play an important role in 6G communication, which are wireless networking, dynamic task allocation, location-based optimization, and energy management [8]. The benefits of the integration of responsive edge-AI services in 6G C-V2X is presented in Fig. 1c. As indicated, the intelligent edge services allow the benefits of co-operative platooning to form a convoy of vehicles in closed and dense spaces [9]. AI-enabled driving controls leverage efficient multi-lane management in highways with low-chances of collisions and lane accidents, photonic-capable intelligent surfaces [10] that send resonating electrical signals to detect obstruction from large distances at high ASV mobility, and dense sensor integration in order of 10^6 sensors/km^2 [3]. To achieve the aforementioned benefits, this paper proposes an edge and AI-enabled resource sharing scheme for C-V2X communications underlying 6G networks.

A. Motivation

The aforementioned discussions highlight the need for effective AI-leveraged edge schemes in C-V2X, with responsive 6G control negotiation at the aggregator and core units. In *Res6Edge*, the fusion of edge-AI in the 6G network addresses the research gaps of training losses, bias convergence at dense sensor interactions. 6G manages a virtual control of physical and link losses, and optimizes the resource sharing channels at low spectral density. Thus, at core edge layers, edge-AI model can be effectively trained to allow co-operative sensing and communication ACVs in local proximity, due to higher available bandwidth. This ensures faster processing of deep models, that optimizes the edge-weights, and it allows the models to stabilize at fewer iterations.

B. Contributions

- We propose a 6G-envisioned layered network model with 6G-aggregator and core units to leverage efficient resource sharing among ACVs in C-V2X communications.
- Based on the proposed 6G layered stack, we propose a resource allocation scheme that serves core requests through a baseband pool (BBU) and forwards them to MBS units.
- To address the mobility, an end-ACV latency and intelligent DRL scheme is proposed for total V2X users, and outputs the caching delay for overall units.

C. Article Structure

The paper is organized into five sections. Section II presents the existing state-of-the-art schemes. Section III discusses the 6G-envisioned intelligent edge-AI scheme to facilitate responsive resource sharing among dense sensor nodes placed over connected smart vehicles in V2X ecosystems. Section IV presents the performance evaluation of the scheme against existing conventional approaches. Finally, Section V concludes the paper.

II. State-of-the-art

In the past few years, various researchers across the globe have given their contributions in this field. For example, Hasan *et al.* [11] highlighted the real-time attacks on systems and different technologies as dedicated short-range communications (DSRC). Later, Kiela *et al.* [12] found the DSRC's distribution of packets during intensive traffic is not efficient with low bandwidth networks. It does not offer security, so, long term evaluation-V2X (LTE-V2X) had been used. Then, Kawser *et al.* [13] discusses the warnings of [12], which was pre-crash sensing, pedestrian, wrong-way direction warnings to avoid/minimize road collisions. Later, Mannoni *et al.* [14] explained the sensors can be for forwarding a warning message to the vehicles about the traffic jams and thus which could reduce both pollution and collisions. Later, Anwar *et al.* [15] presented the applications involving safety as collision, speeding, and also road hazard warnings. Efficient application is mainly for drivers for green wave speed guidance and traffic efficiency. Information service applications include pre-warning messages, route recommendations, improve driving experiences, and traffic information. Table I presents a comparative study of existing state-of-the-art schemes against the proposed scheme in terms of selected computational parameters.

III. *Res6Edge*: The Proposed scheme

This section describes the system model and the proposed scheme.

TABLE I: A comparative study of existing state-of-the art schemes

Author	Year	Objective	1	2	3	4	5	6	7	Application Scenario
Anwar *et al.* [14]	2019	Authors evaluated and compared the physical layer performance of these upcoming technologies for vehicle-to-vehicle (V2V) communications.	✓	✗	✗	✓	✗	✓	✗	Two main applications are discussed as Ultra reliable low Latency Communication (URLLC) and enhanced Mobile Broadband (eMBB) to improve the performance for users.
Kawser *et al.* [13]	2019	Different aspects of V2X communication such as Network Architecture, System requirements, spectrum used etc.	✗	✗	✓	✗	✗	✗	✗	Safety applications to avoid accidents by giving the pre-warning during the collision.
Wang *et al.* [16]	2019	Focuses on the V2X application requirements and its challenges, the need of testing also, discussed different testing methods.	✓	✗	✓	✓	✓	✗	✗	Different applications such as safety, efficiency and information services.
Mannoni *et al.* [14]	2019	Compare both standards by evaluating the performance of both physical layers and associated MAC layers.	✗	✗	✓	✓	✓	✗	✗	Application as pre-clashing/collision sensing is discussed which helps in safety for users
Arena *et al.* [17]	2019	Examine and assess the most relevant systems, applications, and communication protocols that will distinguish the future road infrastructures used by vehicles.	✗	✓	✗	✗	✓	✗	✗	Different applications of vehicles are discussed as V2V safety, Agency environment, and Smart mobility.
Hasan *et al.* [11]	2020	An overview of V2X ecosystem, which includes security issues and defense mechanisms in V2X domain.	✗	✓	✗	✗	✓	✗	✗	Detection of real-world attacks on automotive systems, and different technologies can be used to improve the security.
Do *et al.* [18]	2020	NOMA-based communications between vehicles equipped with multiple antennas over Nakagami-m fading channels in V2X networks.	✓	✗	✓	✓	✗	✗	✗	Quality of Service provided by 5G to improve network throughput and transmission latency which helps user to experience.
Kiela *et al.* [12]	2020	V2X technologies as DSRC and C-V2X are discussed.	✓	✗	✗	✓	✓	✗	✗	Safety, traffic applications which are mainly for user experience are explained with bandwidths.
Proposed	2021	6G-based Edge-AI communication in cellular V2X environments to mitigate end-ASVs latency	✓	✓	✓	✓	✓	✓	✓	Cellular V2X communications supported through 6G-envisioned edge-AI service sets
1. Transmission Latency 2. Transmission Range 3. QoS 4. Data Rate 5. Vehicle Mobility 6. Code Rate 7. Sensor Density										

A. Network Model

In this section, we present the network model of the 6G-envisioned proposed scheme *Res6Edge*, which is depicted in Fig. 2. We consider the entity set E as $\{E_V, E_{RSU}, E_P\}$. The entity E_V be an ACVs defined as $\{V_1, V_2, V_3, \ldots, V_n\}$ also, the entity E_{RSU} be Road Side Units defined as $\{R_1, R_2, R_3, ..., R_k\}$ and the entity E_P be pedestrians defined as $\{P_1, P_2, P_3, \ldots, P_m\}$. The collection of data in V2V communication transmits using orthogonal frequency division multiplexing (OFDM) with different modulations containing channel bandwidth of *10 MHz* and data rate transmission about *27 Mbps*. Thus, the data collection equation is formulated as:

$$\sum_p W^x_{p,i} = d^x_i, \text{where} D \subset n, x \in D, i \in n, \tag{1}$$

where p is the path, $W^x_{p,i}$ tells the flow of vehicles on path p and d^x_i will tell travel demand from i to x, where i is the i_{th} vehicle and x is the particular distance from the vehicle.

$$W^x_{p,i} \geq 0, \text{where}, D \subset n, x \in D, i \in n, \tag{2}$$

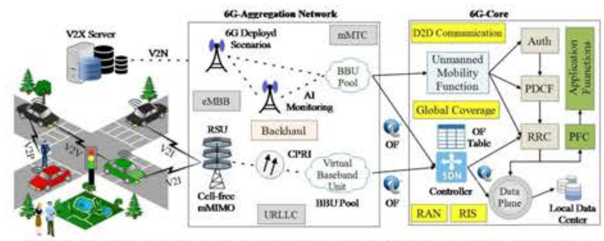
P^x_i tells all the paths through that vehicle. The data transmission in V2P is via wireless communication. Let us consider any particular pedestrian P_p at time t_0, the safety of awareness message for the pedestrian which should be done before collision, thus, the equation depicts the total time as follows.

$$t_0 = \frac{d}{v} - t_p - t_r \tag{3}$$

where, d denotes the distance among the different *V2P* units, and v denotes the velocity of vehicle v. The time t_p is the perception time and t_r is the reaction time of the message that was received by the pedestrian which is called as Cooperative Awareness Messages (CAM). Now, as for transmission of message we require total distance thus it can be formulated as:

$$d_{min} = v * (t_p + t_r + t_d) + gnss_{error} \tag{4}$$

where, t_d is the transmission delay and $gnss_{error}$ is the total error of vehicle and pedestrian communication. Now as all the data collection and transmission is done to fronthaul, cell free massive multiple input and multiple output (mMIMO), i.e. RSIs to backhaul, Virtual baseband unit (BBU pool) where the data is received in the form of fusion at the rate of:



CPRI: Common Public Radio Interface, BBU: Baseband Unit, RSU: Road Side Unit, V2V: Vehicle-to-Vehicle, OF: Open Flow Table V2I: Vehicle-to-Infrastructure, V2P: Vehicle-to-Pedestrian, V2X: Vehicle-to-Everything, Auth: Authentication, PDCF- Packet Data Control Function, RRC - Radio Resource control, PFC- Policy Function Control, RAN: Radio Access Network, RIS: Reconfigurable-Intelligent-Surface

Fig. 2: *Res6Edge*: Network Model

$$R_h = \begin{cases} 0, & \text{if } d_c \geq d_{long} \\ \dfrac{k_p * max(0, proj_v v * u)}{TTC} + k_c, & \text{otherwise} \end{cases} \tag{5}$$

where, R_h is Rate of the message, d_c is the distance of the vehicle, d_{long} is the maximum distance that is feasible by vehicle, k_p tells about gain in longitudinal direction, k_l tells about gain in lateral direction, and $TTC = d_c/Ve_v$ where Ve_v is the velocity of vehicle.

$$\theta_{TA} = h(ID_{TA}||R_{TA}) \tag{6}$$

where, ID_{TA} is the ID of trust authority (TA), R_{TA} is any random number generated through TA, and θ_{TA} is the Unique ID of TA for a particular vehicle. Thus this authenticates the requests and then that will get checked if there are any error or data is relevant thus filtering of data will be done in PDCF after that RRC will take the decision to broadcast this messages containing system information and controls the measurements of the device parameters and thus can be used in different applications.

$$q^c_j(t+1) \leq max(q^c_j(t) - \sum u^c_j(t), 0) + V^c_j(t) \tag{7}$$

where, $q_i^c(t)$ is the total amount of vehicles on road j at time t, $\sum u_j^c(t)$ tells the number of forwarding vehicles and $V_j^c(t)$ this is the number of new arrival vehicles on road j.

$$x_c = \frac{(y_2 - y_1) - (x_2 \tan(\theta_2) - x_1 \tan(\theta_1))}{\tan(\theta_1) - \tan(\theta_2)} \tag{8}$$

$$y_c = \frac{(x_2 - x_1) - (y_2 \cot(\theta_2) - y_1 \cot(\theta_1))}{\cot(\theta_1) - \cot(\theta_2)} \tag{9}$$

where, (x_1,y_1) is the coordinate of the pedestrian and (x_2,y_2) is the coordinates of the vehicle, and θ_1 is an angle from pedestrian and similarly, θ_2 is an angle from vehicle and the final coordinates. Based on the location coordinates, the point of collisions of pedestrian and vehicle units are (x_c,y_c). Thus, the safety of P_p can be located at any given time t, based on CAM message and computed d_{min}, as depicted in eqn. (4).

B. *Res6Edge: The Proposed Scheme*

The section denotes the propose scheme *Res6Edge*. In the scheme, firstly, the 6G-based resource allocation is discussed, and then edge-resource orchestration is discussed. The details are not presented as follows.

1) Proposed 6G resource allocation scheme: This section describes the 6G Resource Allocation scheme in V2X communication as shown in Fig. 3. In this, there are set of user equipment (e.g., vehicles, smart homes, smart cities, mobile users, etc.) considered entity U_e as $[1, x]$ where x is the maximum numbers of users. 6G contains many resources like bandwidth, power, energy, etc. using the D2D links, M2M links and all that resources are sent to the core network (CN) through that to the macro base station (MBS) as shown in algorithm 1.

$$PDR = \frac{Received_p}{Total_p} \tag{10}$$

where, $Received_p$ is the Total number of requests receiving package and $Total_p$ is the total number of requests on the network.

$$SS_e = E_e d_e^{-\beta} h_e 10^{\frac{\epsilon}{10}} \tag{11}$$

where, SS_e is Signal strength of MBS, h_e is gain in channel in MBS, E_e is the transmitting power of MBS, d_e is the distance between device and MBS, β is path loss exponent and ϵ is the Gaussian distributed random variable.

Algorithm 1 Resource Sharing from users to MBS

Input: Collect values of total number of users U_e, and β, E_e, d_e and h_e, li=0, MEC_{min} = 46 dBm .
Output: The list of signal strengths Sf_{li} through which the requests will be forwarded to MBS.

procedure SIGNAL STRENGTH(SS_e)
  $t_1 \leftarrow \beta$
  for $k = 1, k{+}{+}$, while $k \leq x$ **do**
    $t_2 \leftarrow E_k$
    $t_3 \leftarrow h_k$
    $t_4 \leftarrow d_k$
    if $t_2 \geq MEC_{min}$ **then**
      $SS_k \leftarrow t_2 t_4^{-t_1} t_3 10^{\frac{\epsilon}{10}}$
      $Sf_{li} \leftarrow Append(SS_k)$
      li++
    end if
  end for
  output $\leftarrow Sf_{li}$
end procedure

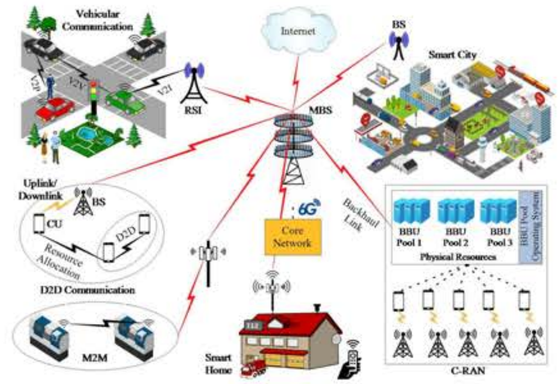


Fig. 3: *Res6Edge*: 6G Resource Allocation

2) Proposed intelligent edge-AI scheme: This describes an intelligence edge-AI services in V2X communication as shown in Fig. 4. The entities E forwards request messages to RSUs, through which the server caches the requests and store them in MEC Server. So, let the total messages required to send be M, and is defined as $mes = (1, 2, 3, \ldots, n_f)$, where n_f are the total messages. The details can be formulated as:

$$M_{mes}^j = \frac{1}{\rho l^{\epsilon}}, \text{where} \rho = \sum_{mes=1}^{n_f} \frac{1}{mes^{\epsilon}}, \tag{12}$$

where the value of j is the particular message to send and here $0 < \epsilon < 1$ is the slope for that message. Now, all the stored messages are sent to backhaul i.e., BBU pool where all the parameters are checked as control, baseband value, Bandwidth of the message, etc. on the BBU Server and thus accordingly resource allocation is done. The caching delay from vehicles and cache server at time t is depicted as follows.

$$T_t^{ca} = \sum_{g=1}^{n_f} x_g^t y_g^t \frac{s}{M_g \overline{R}}, \tag{13}$$

where, T_t^{ca} is the caching delay of the request, $\overline{R}$ is an average transmission between Internet and MEC Server (MEC_O) y_g^t $\in$ (0,1), as the caching decision of vehicle g, where, y_g^t = 0 represents the edge server caches the requested contents, and otherwise y_g^t = 1 and We define the vehicle-to-RSU offloading decision for vehicle g as $x_g^t \in$ (0,1), where x_g^t = 0 represents that vehicle i computes tasks locally, and x_g^t = 1 means tasks are computed remotely at RSUs by traffic offloading. Resource allocation requests are sent to the CN and complex computations are offloaded to cloud servers. Algorithm 2 shows the detailed working of intelligent edge-AI scheme.

The Edge-AI technique takes intelligent decisions thus the learning algorithm we use is deep reinforcement learning (DRL). The reason of DRL adoption is to take adaptive decisions for dynamic environments. DRL performance is considered over RL due to adaptive decisions capability with small search space. In the scheme, DRL is fed with continuous-valued datasets, and the problem is Markov decision process (MDP), that improves the learning rate of the model [19]. In the proposed MDP, the state search space that can be described as follows.

$$sp_t = \{pr_{t-1}^v, pr_{t-1}^v, N_{t-1}, h_{k,t}, h_{k,B,t}, L_t^r, T_t^r\} \tag{14}$$

where, sp_t is the state space, and pr^v_{t-1} tells us the previous

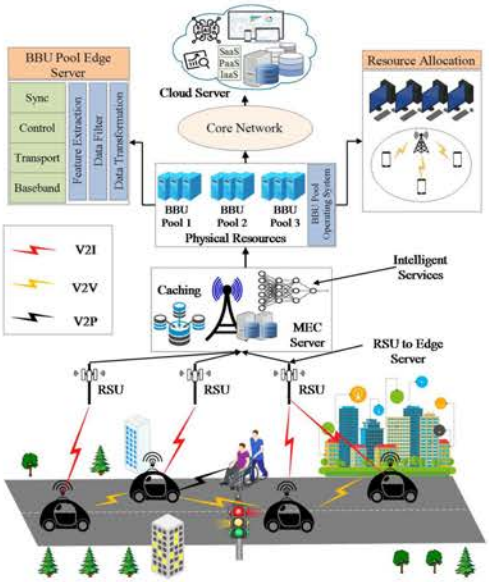


Fig. 4: *Res6Edge*: Edge-AI Services

sub-frame on each RB, L^r_t current load , T^r_t latency threshold this is used for improving V2V communication. The action space of DRL is formulated as follows.

$$2FN_P, p \in \{0, \frac{1}{N_p - 1} P_{max}\} \tag{15}$$

where N_p is the total levels for transmission where $p \in \{0, \frac{1}{N_p-1}\ P_{max},\ \frac{2}{N_p-1}\ P_{max}, \ldots,\ P_{max}\}$ this represents the RB allocation. The action, and reward states can be depicted as follows [19]

1) *Action Space*: The action space for sp_t for every $V2V$ pair is defined as 3-ordered tuple $\{a, sp, t\}$. As $\frac{2}{N_p-1}$ denotes the RB allocation, the power transmission capacity for the communication would require N_p levels. The size of action table is $2FN_p$.
2) *Reward Capacity*: Based on a, the sum capacity of $V2I$ communications are required to be maximized. The reward R_e for any frame f at time t can be depicted as follows.

$$\begin{aligned} R_e = \sum_{r \in R} q_1 R^k_m + \sum_{r \in R} q_2 (R_m - R_{min}) + \\ \sum_{k \in K} q_3 (\gamma_k - \gamma_{th}) + \sum_{k \in K} q_4 G \left(R^k_m - \frac{L^\gamma_t}{T^\gamma_t} \right) \end{aligned} \tag{16}$$

where G denotes the piecewise-linear function, and $\{k_1, k_2, k_3, k_4$ are constants. Each V2V pair observes a joint-mode resource allocation for resource R_e based on Q-table $Q(s, a, \theta)$, where, based on $Q(s, a, \theta)$, the terminal epoch γ with $0 < \gamma < 1$, presents the optimizing conditions of learning rates and rewards in the problem [19].

IV. Performance Evaluation of *Res6Edge*

The section presents the performance evaluation of the proposed *Res6Edge* scheme against baseline 5G approaches for simulation parameters like- obtained vehicular throughput, observed latency, and impact of DRL learning scheme to leverage edge-AI. For the same, the work is compared against baseline 5G approaches for indicated simulation parameters.

A. Experimental and dataset setup

We consider the DSRC Vehicle Communication dataset [20] with 10,000 number of instances. The dataset is divided into two parts as one which contains the jammers who attack while transmission of data to RSUs and the other is the normal part where the data is received at RSUs and also to Users. This dataset contains attributes as Received Signal Strength in dbm, Transmitted node ID number, RSU P-Received, RSU Received Power, Aggregated Throughput, etc. We divided this dataset into training and testing the model. So out of the number of records, we divided as 90% as a training set and 10% as a test set.

Algorithm 2 Intelligence Edge-AI Scheme

Input: Collect values of total number of users n_f, and ϵ, $\bar{R}$, x^t_g, y^t_g, s.
Output: The caching delay of the request T^{ca}_t.

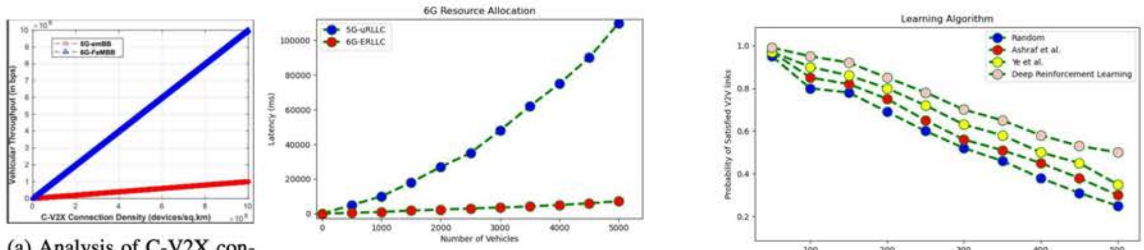
procedure CACHING DELAY(T^{ca}_t)
  for $i = 1, i{+}{+}$, while $i \leq n_f$ **do**
    $t_i \leftarrow \sum_{mes=1}^{n_f} \frac{1}{mes^\epsilon}$
    for (**do**$k = 1, k{+}{+}$, while $k \leq n_f$)
      $M^i_k = \frac{1}{t_1 l^\epsilon}$
      $t_2 = M^i_k \bar{R}$
    end for
    if ($s \neq$ *stored at server*) **then**
      $t_3 \leftarrow$ s
    end if
    for (**do**$j = 1, j++, while j \leq n_f$)
      $t_4 \leftarrow x^t_g\ y^t_g \frac{t_3}{M^i_j}$
    end for
  end for
  $T^{ca}_l \leftarrow t_4$
  output $\leftarrow T^{ca}_t$
end procedure

B. Simulation Results

The section proposed the results for scheme *Res6Edge* for C-V2X Communication, as indicated in Fig. 5. In C-V2X, dense sensor integration are available in E_{ACV}. We measure the vehicular throughput, as indicated in Fig. 5 (a) for 10^8 connected sensors among E_{ACV} in a communication range. We consider the baseline 5G-emBB approach and compare the results to further emBB (FeMBB), due to better service orchestration of 6G compared to 5G. 6G envisions a user experience data rate 10 times of 5G services, which is evident in the figure. At 4×10^8 connected sensors, the vehicular throughput in 5G is 0.7 Mbps. In 6G, the obtained throughput is close to 43.24 Mbps. As CAM messages are propagated effectively in 6G channels, the obtained throughput is higher.

Fig. 5 (b) tells about the comparison of 5G uRLLC service against 6G enhanced reliable low-latency communications (ERLLC), on the basis of increase in E_{ACV}, against measured latency. As evident, as the number of vehicles increases the latency increases exponentially for 5G scheme, but the increase is subdued in 6G-V2X channels, for 1500 vehicles. The measured average latency for 5000 Vehicles is 48000 milliseconds (ms) for 5G services and is reduced to 3470 ms in 6G respectively.

In Fig. 5 (c), DRL is used ad the intelligent edge-AI scheme to improve the quality of service (QoS) guarantees to end user. For V2V links, we measure the impact of the learning scheme against conventional approaches. We have compared the work against random-access models, Ashraf *et al.* [21]



(a) Analysis of C-V2X connection density for proposed 6G scheme

(b) Comparative analysis of V2X latency with baseline 5G-uRLLC scheme

(c) V2V satisfaction probability using DRL

Fig. 5: Simulation Results of *Res6Edge* scheme

and Ye *et al.* [22]. It is evident that as number of E_{ACV} increases, the probability of satisfied V2V links decreases as the complexity of links increases. The same is depicted in Fig. 5 (c). For 50 vehicles, the probability is close to 0.98, and in case of 500 vehicles, the obtained satisfaction probability is close to 0.5, which is significantly higher, compared to 0.35 in Ye *et al.* [22], and 0.30 in Ashraf *et al.* [21]. Thus, DRL is a suitable candidate for edge-AI resource selection in C-V2X based ecosystems, as it reduces the complexity of the overburdened links through trained accuracy.

V. Conclusion

The paper highlights a 6G-envisioned edge-AI enabled resource sharing scheme, *Res6Edge*, for modern C-V2X communications. 6G in C-V2X addresses the limitations of dynamic resource provisioning to edge nodes, at extreme low-latency, high availability, and dense connection throughput. In *Res6Edge*, edge-AI is integrated with 6G network channels, that address the research gaps of intelligent and dynamic resource orchestration for edge ACV nodes. To exploit the key enablers for resource allocation, we proposed a 6G-stacked model with a built-in CAM service that operates on mMIMO BBU backhaul units. BBU units leverage the 6G-aggregator units functionality and support MBS based resource communication. At the 6G core, we envision edge-AI service sets that allow D2D local proximity cache and lower the processing delay. To improve the task locality, a DRL learning scheme is proposed to scale to large-scale ecosystems. The obtained results indicate the viability of the proposed scheme.

In the future, we would formulate a Markovian based decision model for DRL that improves the learning rate of the model at fewer iterations, and minimize the bias through optimization strategies in search space. This will improve the overall precision and accuracy of the edge-AI learning at comparatively less number of epochs, and form a resilient C-V2X infrastructure.

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