Resource Allocation Enablers and Allocation for Beyond 5G Vehicle-to-Everything Systems

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***Abstract*—In the modern era of widespread wireless devices and their underlying connectivity requirements in the Internet of Things, efficient use of resources across networks is inevitable. The 5G emerging techniques aim to equip each application with advanced features and to make connectivity between the devices ubiquitous. Therefore, the Resource Allocation (RA) in the 5G and 6G networks has gained more research traction to use the sparse resources in the wireless channels effectively. In Vehicular communication encompassing autonomous driving, there is a need to embed the Multi-Radio Access Technology (Multi-RAT) to form Heterogeneous Networks (HetNet) and meet the diverse network requirements. Thus, this paper provides an overview of the resource allocation enablers and methods for Beyond 5G (B5G) Vehicle-to-Everything (V2X) systems. It begins by discussing the key features of B5G V2X systems, such as the slicing RA technique. The paper then proposes and describes a taxonomy that represents the enablers of RA in B5G V2X systems in the network and physical layers. The paper also discusses various allocation methods used as keys of 6G networks, such as machine learning algorithms, deep learning algorithms, and management modelling, such as graph and game theories. At the end of this paper, some open research challenges are discussed, such as the efficient use of machine learning algorithms in RA and virtual RA backhauling.**

***Keywords*—resource allocation, Beyond 5G, 6G, Vehicle-to-Everything (V2X), Multi-Radio Access Technology (Multi-RAT)**

I. Introduction

The world is progressing toward higher connectivity needs between devices. There is a need to make connectivity ubiquitous to ensure a smooth flow of information between the devices [1]. Vehicular communication is one of these advanced networks that aim to connect vehicles anywhere and anytime with everything along the road and the surrounding areas, encompassing the communication between Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Networks (V2N) [2]. These networks can be combined in one name called Vehicle-to-Everything (V2X) networks, which assist in relaying information, improving road safety, broadcasting awareness and warning messages, providing a better travel experience, reducing traffic congestion, and establishing intelligent networks to reach autonomous driving [3]. To ensure clarity, the acronyms used in this study are summarized and presented in Table I.

In the context of Beyond 5G (B5G) and the evolution of communication networks specific to V2X applications, several types of networks are being explored in this paper, such as:

A. Cellular V2X (C-V2X)

C-V2X is designed to enable direct communication between vehicles and infrastructure using cellular networks. It includes both short-range direct communication and long-range communication.

B. Ad-Hoc V2X Networks

Ad-hoc V2X networks involve direct vehicle communication without relying on a centralised infrastructure. This type of network is especially useful in scenarios where communication needs to occur quickly and without depending on a fixed infrastructure.

Mesh networks are a special type of ad-hoc V2X that involve vehicles forming a dynamic mesh where each vehicle acts as a relay point for others. This helps extend

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the communication range and improve reliability, especially in areas with limited infrastructure.

C. Multi-Access Edge Computing (MEC)

As one of the cloud networks, MEC involves placing computing resources at the edge of the network, closer to the V2X communication endpoints.

D. Software-Defined Networking (SDN) and Network Function Virtualisation (NFV)

SDN and NFV technologies can provide a more flexible and programmable network infrastructure, allowing for the dynamic allocation of resources based on V2X communication demands.

TABLE I. LIST OF ACRONYMS USED IN THE STUDY

Acronyms	Definitions	Acronyms	Definitions
5G	Fifth Generation	6G	Six Generation
ACC	Adaptive Component Carrier	AI	Artificial Intelligent
APS	Adaptive Packet Scheduling	ATOA	Adaptive Task Offloading Algorithm
B5G	Beyond 5G	CA	Channel Assignment
CNN	Convolutional Neural Network	CRRM	Cooperative Radio Resource Management
CSI	Channel State Information	D2D	Device-to-Device
DL	Deep Learning	DNN	Deep Neural Network
DSRC	Dedicated Short-Range Communication	eMBB	Enhanced Mobile Broadband
GCS	Global Cloud Server	GS	Gale-Shapley
GWS	Gateway Server	HetNet	Heterogeneous Network
ICI	Inter-Channel-Interference	IoT	Internet-of-Things
ISI	Inter-Symbol- Interference	ITS	Intelligent Transportation Systems
LIS	Local ISP Server	LSTM	Long Short-Term Memory
LTE	Long Term Evolution	MDP	Markov Decision Process
MDP-PS	Markov Decision Process-based Cost Reward Packet Selection	MEC	Mobile Edge Computing
MIMO	Multiple-Input Multiple-Output	ML	Machine Learning
MLB	Mobility Load Balancing	NANS	Network Assisted Networks' resource Selection
NFV	Network Function Virtualisation	PA	Power Allocation
PAWAS	Power Allocation with Antenna Selection	PHY	Physical Layer
PSO	Particle Swarm Optimisation	QoS	Quality of Service
RA	Resource Allocation	RAN	Radio Access Network
RAT	Radio Access Technology	RL	Reinforcement Learning
RSU	Roadside Units	SDN	Software-Defined Networking
ST-KNN	Space-Time k-Nearest Neighbour	TDD	Time Division Duplex
URLLC	Ultra-Reliable Low Latency Communications	V2I	Vehicle-to-Infrastructure
V2N	Vehicle-to-Network	V2P	Vehicle-to-Pedestrian
V2V	Vehicle-to-Vehicle	V2X	Vehicle-to-Everything
VANS	Vehicular cognitive radio Node Assisted Networks' resource Selection	WLAN	Wireless Local Area Network

These network types are designed to address the specific requirements of V2X communication, including low latency, high reliability, and the ability to support a massive number of connected devices.

V2X communication makes city traffic control safer by enabling Intelligent Transportation Systems (ITS) [4]. These networks use existing Internet of Things (IoT) networks and effectively utilise available resources. Researchers in academia and industry are working to improve V2X communication by using existing vehicular networks and enabling technologies like Dedicated Short-Range Communication (DSRC) and Long-Term Evolution (LTE) [5]. Combining these networks can overcome the challenges of IEEE 802.11p, such as hidden Roadside Units (RSU), short communication, and high data rate requirements [6]. It also addresses the challenges of LTE by allowing for broadcasting messages to surrounding vehicles and providing the fastest V2V links [7]. Combining these two networks creates a heterogeneous network (HetNet), as shown in Fig. 1, which allows small-cell configurations to be used in vehicular networks. HetNet has been seen as a promising setup for improving the efficiency, capacity, scalability, reliability, and low-latency communication of V2X [8]. However, a high number of microcells in the network can lead to congestion and high demands on resources such as power, spectrum, time, and signalling control [9], especially in 5G and Beyond 5G (B5G) networks due to the growing number of requests for network connectivity during travel [10]. Therefore, using efficient Resource Allocation (RA) techniques is crucial for efficient communication, offloading, and scheduling.

Both DSRC and LTE have their techniques for allocating resources [11]. The techniques used in DSRC include packet collision modelling, throughput modelling, mobility-based access modelling, priority-based allocation, and exhaustive search, particularly for mobility networks [12]. For the LTE network, the techniques used are Graph theory, Karush-Kuhn Tucker Theory, Perron-Frobenius Theory, Semi-Markov Decision Process, Greedy algorithm, and Lyapunov Optimisation. These techniques form the foundation of HetNets with necessary improvements [13].

All these RA techniques and models should meet the B5G system's requirements. This means that it is helpful to use these techniques and models if they overcome and take into consideration the following challenges:

- B5G systems depend on highly dynamic scenarios where vehicular speed could exceed 500 km/h [14]. Thus, the RA algorithm shall incorporate low to high-mobility vehicular ranges. The proposed RA algorithm shall also cater to the effect of Doppler spread/shifts and multi-path fading channels [15].

- B5G systems are expected to support a wide range of data services such as infotainment, security, video streaming/gaming, Internet browsing, and information exchange between vehicles. These services require efficient RA algorithms to ensure ultra-reliable and low-latency communication, high throughput, and efficient spectrum to satisfy the Quality-of-Service (Qos) requirements [16].
- The several kinds of services that B5G networks cover are to be ensured in Radio Access Technology (RAT) under the tri-band cell configuration. Using multi-RAT becomes more attractive in advanced networks like V2X because it offers low latency and high throughput communication. However, the need for efficient RA algorithms and techniques is also indispensable to meet multi-RAT requirements including the control signalling that leads to the use of advanced RA enablers and models such as Software-Defined Network (SDN), slicing, Machine Learning (ML) algorithms, and Deep Learning (DL) algorithms [17].

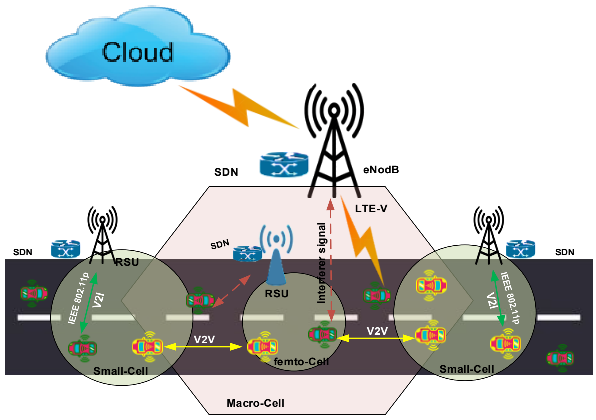


Fig. 1. Multi-RAT HetNet configuration.

The main goal of this overview paper is to provide a detailed explanation of the advanced technologies and promising allocation models that can address the challenges and requirements of B5G systems.

E. Existing Overviews

Considering the aforementioned challenges as a baseline, and the ultimate objective of attaining efficient RA in the fast-changing dynamic networks, designing novel algorithms in DSRC and LTE is essential [18]. Some of the underlying techniques that complement the design of new models for RA are cognitive networks [19], ultra-dense networks [20], and massive Multiple-Input Multiple-Output (MIMO) [21].

Many surveys review the RA techniques and algorithms in vehicular communication [22], For instance, introduces vehicular networks in light of the network requirements and the existence of enabling technologies in the context of LTE Device-to-Device (D2D) Communication. Another survey aimed at V2X communication considers the requirements of the networks, various modes including the LTE-D2D communication, and the existing RA algorithms used [23]. These have been summarised in Table II.

One potential limitation of the two surveys presented above is their non-inclusion of the RA techniques used in IEEE 802.11p, and instead have focused only on LTE-D2D communication. Additionally, the spectrum of techniques reviewed is limited and does not incorporate Machine Learning and network slicing, which are becoming essential in limited resources. These limitations have been overcome in Ref. [24], which provides a comprehensive survey on RA techniques in both vehicular networks, IEEE 802.11p and LTE-V2X. Further, it covers the RA techniques suitable for the HetNets. In the context of RA improvements, ML/DL and slicing techniques have also been discussed in Ref. [24].

Nevertheless, some of the essential parts that have not been covered involve using SDN, Network-Function Virtualisation (NFV), and cloud computing to improve RA techniques. Thus, we have focused the work in this study on reviewing all the essential techniques for improving RA for the B5G networks. These include the small cell configuration and smart communication using massive MIMO, beamforming, slicing, ML, and DL.

F. This Overview

This overview provides an in-depth examination of Resource Allocation (RA) techniques in B5G and emerging 6G networks, focusing on their applications within Vehicle-to-Everything (V2X) systems. The primary objective is to offer a comprehensive understanding of current and promising RA techniques in B5G while exploring advancements anticipated in 6G. The main contributions of this overview are:

- We present and investigate recent network configurations used in B5G vehicular communication, such as the HetNet, which includes the small-cells topology, multi-RAT, and smart communication using ML and Artificial Intelligence (AI), SDN, Network Slicing, and Cloud Computing to decrease latency in the RA process.
- Building upon B5G, this review also explores emerging 6G paradigms. These incorporate advanced ML techniques like federated learning, graph neural networks, and blockchain-based approaches for RA. These technologies are anticipated to significantly enhance RA's flexibility, security, and efficiency, particularly in scenarios with high mobility and low-latency requirements.
- A taxonomy for the RA process has been derived in the vehicular communication context based on different parameters such as enablers, allocation techniques, and computation.
- The review culminates by highlighting several open research challenges and suggestions for applying efficient RA in HetNet.

The work is structured as follows: Section II discusses recent network configurations used in vehicular B5G, such as smart communication based on HetNet and multi-RAT to enhance their performance and network slicing. A taxonomy based on different parameters is presented in Section III. Section IV introduces some open research challenges toward efficient B5G systems RA, such as virtual backhauling and autonomous RA. The potential of 6G in overcoming RA challenges is presented in Section V. Finally, the conclusion and future recommendations are presented in Section VI. The work structure is shown in Fig. 2.

TABLE II. RA TECHNIQUES IN LITERATURE

Ref.	Taxonomy	HetNet.	ML/Slicing	SDN / Cloud	Remarks
[22]	✗	✗	✗	✗	Study the RA of the LTE-D2D network only without involving the HetNet configuration.
[23]	✓	✗	✗	✗	A Taxonomy of the RA techniques used in the LTE-D2D network has been presented.
[24]	✓	✓	✓	✗	Provides a taxonomy of the HetNet with some mention of the use of ML algorithms and slicing methods to perform RA in vehicular communication.

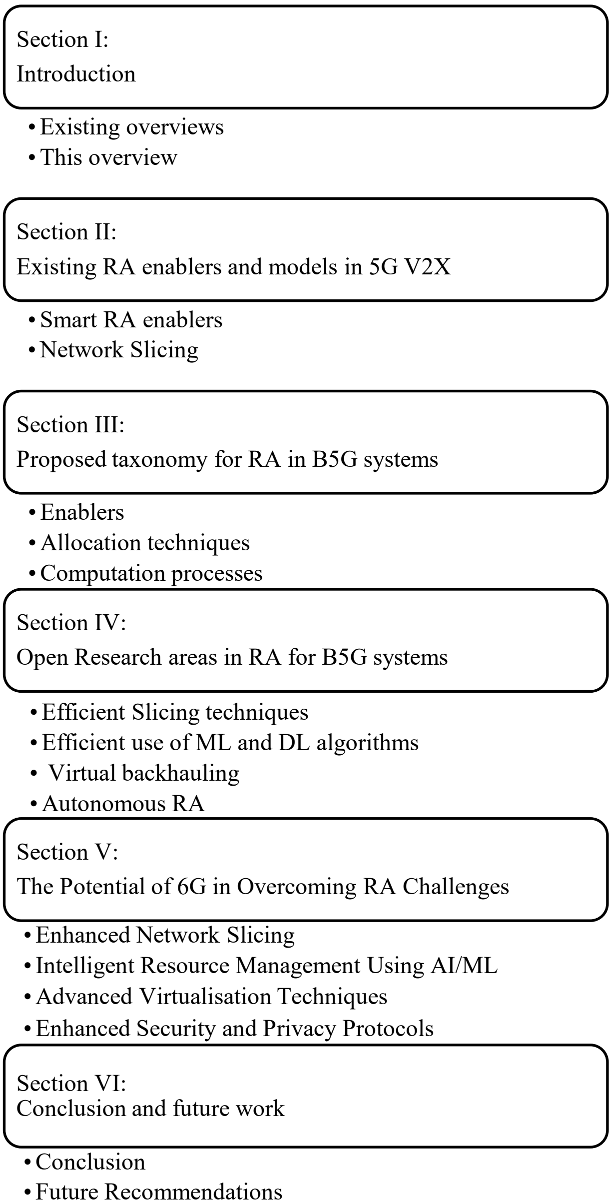


Fig. 2. Structure of the overview.

II. EXISTING RA ENABLERS AND MODELS IN 5G V2X

This section examines the current state of RA enablers and methods in 5G networks and delves into the specific enablers and methods used for RA in V2X. The discussion covers the utilisation of advanced techniques for RA in V2X and the implementation of network slicing enablers as used in 5G technology. The details of these topics are presented in the following paragraphs:

A. Smart RA Enablers

Multi-RAT utilisation in 5G networks necessitates implementing holistic RAT management to effectively allocate network resources, particularly when small-cell configurations are used [25]. This management process requires advanced techniques such as SDN and NFV to manage resources efficiently. SDN enables centralised control of the network and provides a comprehensive view of the network, but the challenge is the increased latency caused by signalling through a centralised controller. A potential solution is the use of distributed SDNs [26].

Additionally, an efficient routing method between SDNs is needed to facilitate control. Cloud computing is increasingly being used to ensure real-time computation and management of resources, as it allows for decentralised processing while utilising fewer infrastructure components. Efficient resource allocation enablers also aim to decrease energy consumption and execution time through heuristic algorithms [27].

The proposed work in Ref. [28] focuses on determining the amount of traffic data and scheduling the order of each RAT to achieve a balance between the vehicle's speed and required traffic data, leading to a decrease in energy consumption and allowing for offloading between RATs.

Similarly, the work in Ref. [29] proposes cloud Cooperative Radio Resource Management (CRRM) in HetNet, which enables resource allocation between various types of networks such as cellular and Wireless Local Area Networks (WLAN), resulting in increased throughput and decreased latency when transitioning between RATs. A summary of the above-mentioned works is presented in Table III.

B. Network Slicing

Recently, one of the most significant developments in the RAT infrastructure of 5G networks is network slicing, which involves dividing the network into several smaller networks, each designed to serve specific applications. Network slicing is highly relevant in 5G and beyond networks.

Multi-RATS are divided into slices, each dedicated to specific applications such as WLAN for infotainment, LTE for cellular applications, and IEEE 802.11p for short-range communication and broadcasting of information [30]. This technique is efficient regarding Resource Allocation (RA) as it saves resources such as power consumption and spectrum optimisation due to the specific operations of each slice.

By implementing the network slicing technique, resources can be allocated efficiently in segments, where each slice or group of slices is intended to perform a specific task [31]. This technique includes various slicing cases, as well as the allocation of resources in the core network, known as the core network slice, and the Radio Access Network (RAN) segment called the RAN-slice [32]. The aim is to improve the Qos across each slice of the network. ML and DL algorithms are used to allocate resources across slices.

Additionally, other techniques such as Markov Decision Process-based cost reward Packet Selection (MDP-PS) [33], Adaptive Packet Scheduling (APS) [34], and Adaptive Component Carrier scheduling (ACC) [35] are also used to allocate resources for each slice to increase network throughput. Another approach is to slice the network according to vehicle requirements.

This method divides the network into two parts: a slice for high throughput requirements connected to enhanced Mobile Broadband (eMBB) and a slice for safety/emergency requirements connected to Ultra-Reliable Low Latency Communications (URLLC). This reduces computation and network switching using the Gale-Shapley (GS) algorithm [4] to achieve a stable matching between URLLC and eMBB connections with low computational complexity. A similar study has been presented in Ref. [25], focusing on edge users, which poses a challenge.

Using cloud computing, combining Mobile Edge Computing (MEC) and network slicing can offer efficient RA for edge users. This combination allows for the efficient offloading of data from one slice to another without compromising their effectiveness. All of these mentioned works are summarised in Table IV.

TABLE III. SUMMARY OF THE RECENT ADVANCEMENTS IN SMART COMMUNICATION TECHNIQUES

Reference	Feature	Merit
[28]	Using the cloud to enable online computation decreases the connection latency when using SDN. Allows scheduling between the available RATs using heuristic algorithms.	Reducing energy consumption. Reducing the execution time.
[29]	Cloud Cooperative Radio Resource Manager (CRRM) is used to allow efficient use of the spectrum available between two different networks. Increasing throughput of the communication and decreasing the latency of the connection when travelling between one RAT to another.	Allow real-time resource allocations across multiple RATs.

TABLE IV. SUMMARY OF THE NETWORK SLICING RECENT ADVANCES

Ref.	Feature	Merit
[35]	Reinforcement learning is followed by a low-complexity heuristic algorithm. Maximising resource utilisation while ensuring the availability of resources.	Allocate resources for each slice.
[34]	Several types of ML algorithms are used to perform slicing.	To increase the throughput of the network
[36]	Slicing the network into eMBB slice and URLLC slice.	Requirement-aware RA
[25]	Combining MEC and Slicing to serve edge users.	Requirement-aware RA

C. Future RA Enablers and Models in 6G V2X

The 6G communication is the next ground-breaking technology anticipated to enhance existing RA enablers' developments. The 6G communication networks are fundamentally built upon the principles of 5G [37], yet with the incorporation of new technologies such as AI-driven RA, quantum communication, and Terahertz (THz) communication [38, 39]. These components will enable ultra-fast, reliable connectivity to enhance RA efficiency and support for various V2X applications.

1) AI-Driven RA and autonomous management

The 6G networks are anticipated to extensively use AI and machine learning for RA optimisation in real-time. Advanced techniques like Deep Reinforcement Learning (DRL) and Federated Learning (FL) [40, 41] in RA will allow autonomous decision-making that can lead to their adoption in highly dynamic V2X environments with minimal latency. Compared to the SDN approach in 5G the 6G technologies will rely on a more distributed AI framework [42]. The AI agents will operate locally on the edge nodes to improve latency and scalability. This will reduce the reliance on the central controllers [43]. The AI-driven RA enablers will be able to efficiently handle massive data influx from the 6G V2X due to a predictive analysis capability. The predictive analysis can help forecast the resource needs per the vehicular movement patterns, allowing a proactive RA. This will enable seamless and stable connections while the vehicles navigate several network zones [44, 45]. FL will help mitigate privacy concerns as the data will be kept decentralised. This will be critical for handling sensitive user information.

2) Quantum communication and RA

Quantum communication is anticipated to play a critical and significant role in 6G V2X. This will help offer improved security and faster data transmission rates. The Quantum Key Distribution (QKD) can be integrated along the RA mechanisms to allow secure communication channels [46]. This is particularly important for the mission-critical V2X application, including autonomous driving and emergency vehicle coordination [47]. The quantum-assisted RA models can curtail the computation times in real-world environments. This can help optimise the RA process for URLLC.

3) Terahertz (THz) communication and RA

The 6G technologies will potentially operate in the THz spectrum, which allows immense bandwidth that allows multi-gigabit data rates and ultra-low latency. Such high-frequency THz bands are well suited for short-range high-speed V2X communication. Nevertheless, RA in the THz spectrum requires sophisticated beamforming and dynamic frequency allocation strategies for handling path loss and signal attenuation issues [48]. Adaptive RA mechanisms will become in place to utilise THz beams and AI-controlled beam tracking to cater to this. This will enable connectivity between rapidly moving vehicles.

4) Network slicing and blockchain for enhanced security

6G will extend upon the slicing capabilities for dynamic slice management. Integrating blockchain in 6G slices will help achieve a higher level of security. The dynamic creation of the slices will help support several applications that range from Ultra-High Definition (UHD) to real-time safety communication. The enablement of decentralised trust management across the slices will help maintain multislice applications in the V2X communication [49, 50].

Blockchain-based RA models can provide decentralised trust management across slices, which is essential for V2X applications involving multiple stakeholders.

A summary of the future RA enablers and models in 6G V2X has been presented in Fig. 3.

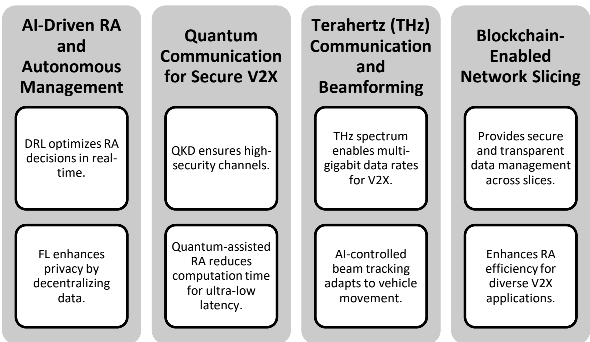


Fig. 3. Future RA Enablers and Models in 6G V2X.

D. Adaptive Resource Allocation Models for Real-Time Data and Dynamic User Behaviour

Effective handling of dynamic user behaviour is imperative for real-time vehicular communication. The RA models for the B5G system use advanced algorithms using predictive and adaptive methods. Such models use Reinforcement Learning (RL) and Markov Decision Processes. Such models allow adaptive decision-making in real-time using CSI and user mobility patterns.

The RA models incorporate low-latency computation layers. These involve Mobile Edge Computing (MEC) for processing real-time data generated by the V2X communication endpoints. The model uses decentralised decision-making based on software-defined radio and federated learning. This reduces the reliance on central controllers and thus improves the processing efficiency.

The dynamic user behaviours introduce variability in the resource requirements. This is due to several factors, including vehicle speed, traffic density, and infotainment service demands. RA models address these challenges by integrating adaptive techniques such as channel independence and user-centric interactive models.

III. Proposed Taxonomy for RA in B5G Systems

In the realm of V2X networks, the integration of millimetre/terahertz communications, cell-free Massive MIMO, and short packet communications represents a transformative leap towards enhancing the efficiency and safety of connected vehicles. Millimetre/terahertz communications leverage higher frequency bands to provide wider bandwidths, facilitating faster data transfer and lower latency.

This technology supports critical applications such as high-definition mapping and real-time sensor data exchange.

Simultaneously, cell-free Massive MIMO redefines traditional cellular networks by fostering dynamic collaboration among multiple access points. This approach enhances coverage, capacity, and the seamless handover of connected vehicles, particularly in complex urban environments.

Short packet communications, designed for swift and efficient transmission of safety-critical messages, play a crucial role in ensuring that vital information, such as collision warnings and emergency braking signals, is relayed promptly between vehicles and infrastructure. As these innovations converge, they contribute synergistically to the evolution of V2X networks, promising a future where connected vehicles operate with unprecedented levels of safety, reliability, and real-time responsiveness. Mmwave has emerged in the discussion of beamforming as an enabler in this paper, cell-free massive MIMO has emerged in the discussion of small-cells massive MIMO, and the short packet communication has emerged in the discussion of distributed SDN, small-cells massive MIMO and channel assignment.

As depicted in Fig. 4, a proposed taxonomy has been illustrated in this section using enablers that are used to allow efficient RA in B5G systems, the allocation techniques and methods, and the computation process used to assist RA.

A. Enablers in B5G Systems

Enablers of RA for B5G systems depend on on-demand computing apart from some generic programmable hardware such as SDN, as shown in Table V. On-demand computation depends on using cloud computing in the whole network and Fog/MEC for the edge users [51]. Because of this, enablers of the RA can be classified into two main parts: First, the network topology comprising hardware implementation such as SDN and slicing, and software computation such as NFV, cloud computing, Fog, and MEC computing. Second, the class of enablers is the PHY layer configuration comprising three promising configurations, including massive MIMO, small-cell configuration, and beamforming to mitigate interference [52].

Each type of enabler has its advantages and challenges. An SDN controller is the easiest and most effective way to enable RA. It can be used in three configurations: the centralised control plane, the distributed control plane, and the hybrid control plane. The easiest use is centralised, requiring only one SDN to view complete network operations and data flows. This will decrease the establishment cost below the cost of using distributed configuration, but with the increase in the overhead of the traffic data [53].

However, using distributed SDNs can decrease the traffic flow latency and the overhead on the central SDN. An efficient routing algorithm is required to exchange data between SDNs. This results in a waste of power consumption [54]. To overcome the wastage in RA, a hybrid configuration of SDNs can be used, such as reducing the power consumption and increasing the offloading, leading to an increase in throughput and capacity. Nevertheless, efficient routing protocols are essential in hybrid networks [55].

However, using NFV permits the employment of virtual machines and networks to implement any function on the existing hardware. This renders no requirement to use additional hardware to modify the configuration in RA. The work depends on allowing virtual computation using the same SDN controller [28].

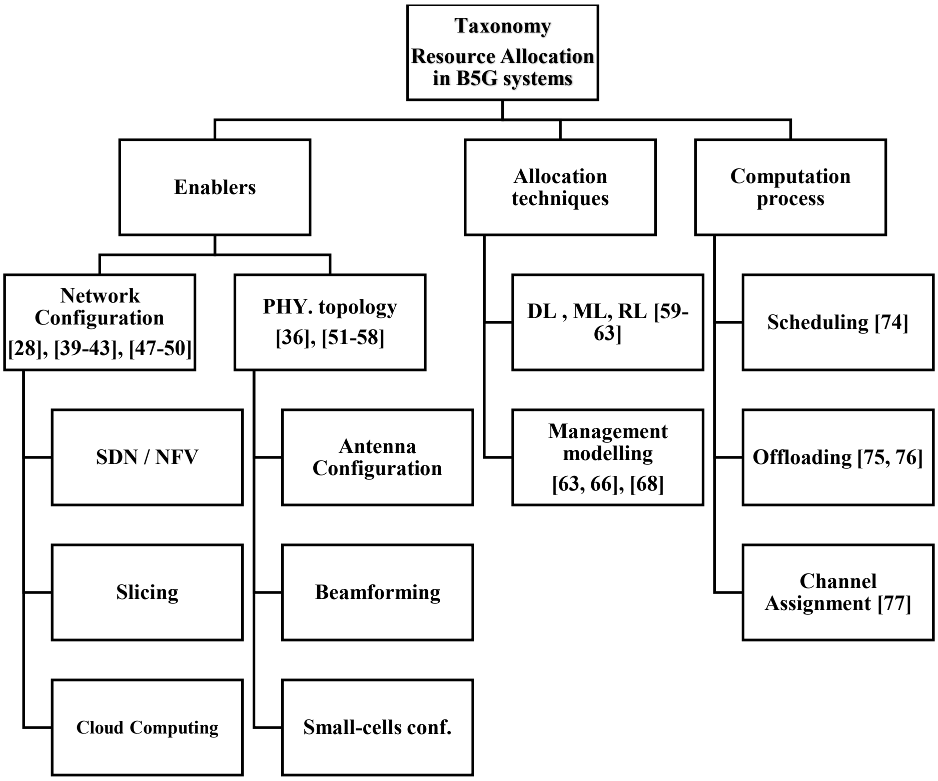


Fig. 4. Proposed taxonomy for RA in B5G systems.

As alluded to earlier, the use of a hardware controller has an impact on infrastructure costs. By using on-demand computational RA, the use of cloud computing becomes essential [56]. It is helpful to employ cloud computing in large-scale networks where all traffic flow processes are handled in the cloud, decreasing the overhead on the physical network [57]. There are many techniques used in cloud computing to allocate the resources available in the network such as Global Cloud Server (GCS) [58], Local ISP Server (LIS) [59], Gateway Server (GWS) [60], Vehicular cognitive radio Node Assisted Networks' resource Selection (VANS) [61], Network Assisted Networks' resource Selection (NANS) [62], and fuzzy rule-based scheme to eliminate the inappropriate cloudlets before deciding an optimal cloudlet to be used. This helps minimise handover delay, packet loss, average queuing delay, and device lifetime in a network [63].

Slicing is a promising network topology used for future vehicular networks. Ye *et al.* [64] discussed the use of slicing in high mobility networks where any challenges impinge upon RA due to an abruptly changing environment, and thus the stochastic environment changes. They develop an online slicing scheduling strategy for RA in vehicular networks, leveraging Lyapunov optimisation to allocate power control at each time slot according to the current network state. This will maximise the capacity and guarantee the Qos requirement, such as ultra-reliable and low-latency vehicle communication links.

The second main class of enablers is the PHY layer configuration. It comprises three main technologies: massive MIMO, small-cell configuration, and beamforming [21]. Cheng *et al.* [36] proposed the combination of small cells in virtual form and directional beamforming to mitigate interference between small cells and between small cells and macro-cells used to increase system capacity and reduce site cost. They employ a user mobility prediction model using a Q-learning algorithm to find the optimal user association and RA strategy, leading to better performance for many users. The same concept of small-cell configuration is used in Ref. [65] with some consideration on load balancing between them using Mobility Load Balancing (MLB) to transfer load from an overloaded small cell to under-loaded neighbouring small cells for a more load-balanced network.

Two-tier HetNet architecture is proposed in Ref. [66] to overcome the challenges of high density and mobility in vehicular communications. The configuration depends on the main macro-cell and the number of small cells with pre-allocated persistent resources to small cells based on predicted traffic using a Space-Time k-Nearest Neighbour (ST-knn) method to shorten the signal travelling. In contrast, Kumar and Kumar [67] generalized the concept of small cells to dense groups of femtocells that reduce the RA's complexity and enhance the required Qos. It uses the Particle Swarm Optimisation (PSO) algorithm based on game theory because of its stability in forming the clusters.

Massive MIMO and beamforming are two methods of allocating resources in future networks. Jamil *et al.* [68] used the Power Allocation with Antenna Selection (PAWAS) technique to enhance energy efficiency by considering the channel state and traffic density. Mardi *et al.* [69] uses efficient clustering to have resource management techniques to attain spectrum sharing and power control that relies on large-scale fading. This technique can be used in hybrid networks between cellular and DSRC to improve cellular user sum rate, the average packet received ratio and throughput.

TABLE V. SUMMARY OF RA ENABLERS IN B5G SYSTEMS

Ref.	SDN Controller	NFV Integration	Cloud Computing	Slicing	PHY Layer	Key Findings	Complexity	Computation Cost
[54]	✓	–	–	–	–	Distributed SDN reduces latency but requires efficient routing algorithms.	High	The need for efficient routing algorithms
[55]	✓	–	–	–	–	Hybrid SDN enhances throughput but relies on efficient routing.	Moderate	The need for efficient routing algorithms
[53]	✓	–	–	–	–	Centralised SDN provides holistic network visibility but with increased traffic data overhead.	High	Increased traffic data overhead.
[28]	–	✓	-	–	–	NFV reduces hardware dependency but requires a virtual computation layer.	Low	More virtual layers needed
[56]	–	–	✓	–	–	Cloud improves network capacity but raises latency concerns.	Low	Latency concern
[61]	–	–	✓	–	–	Fuzzy routing eliminates inappropriate cloudlets but introduces computation complexity.	Moderate	Latency concern when using Fuzzy routing
[64]	–	–	–	✓	–	Power control in slicing enhances dynamic allocation but faces challenges with high mobility.	Moderate	Increase of complexity when high mobility is available
[36]	–	–	–	✓	–	Mobility prediction in small cells with beamforming increases system capacity.	Low	The traffic load on each cell. Needs of cell-free massive MIMO
[65]	–	–	–	✓	–	Mobility load balancing reduces overload but requires efficient techniques.	High	The need for efficient routing algorithms
[66]	–	–	–	–	✓	Mobility prediction in small cells decreases overload through resource pre-allocation.	Moderate	The traffic load on each cell. Needs of cell-free massive MIMO
[67]	–	–	–	–	✓	Clustering in small cells enhances energy efficiency but introduces computation overhead.	High	The need for efficient routing algorithms
[68]	–	–	–	–	✓	Power control in Massive MIMO enhances energy efficiency but faces complex computation.	High	Increase of complexity when high mobility is available
[69]	–	–	–	✓	✓	Power control in Massive MIMO improves packet ratio and throughput with complex computation.	High	Increase of complexity when high mobility is available
[70]	–	–	–	–	✓	Power control in Massive MIMO reduces inter-beam interference but requires complex computation.	High	Increase of complexity when high mobility is available
[71]	–	–	–	–	✓	Massive MIMO enhances spectral efficiency but limits range due to mmWave use.	Moderate	Limited range of communication

TABLE VI. SUMMARY OF RA TECHNIQUES

Ref.	RA technique	RA concern	Algorithm
[72]	DL	Network slicing	LSTM
[73]	DL	Network slicing	CNN
[74]	ML	Vehicle behaviour and mobility	DNN
[75]	Management modelling + RL	Packet scheduling decision	Markov Decision Process + Q-learning
[76]	RL	HetNet with online computation	Q-learning
[77]	Management modelling	Vehicle behaviour and mobility	Graph theory
[78]	Management modelling	Vehicle behaviour and mobility	Lyapunov Optimisation
[79]	Management modelling	Vehicle behaviour and mobility	Semi-Markov Decision Process
[80]	Management modelling	Vehicle behaviour and mobility	The game-theoretical strategy optimisation algorithm

Bates [70] and Gupta and Kumar [81] summarised the use of massive-MIMO in fast data transmission service in a high-mobility wireless communication system using imperfect Channel State Information (CSI) and beamforming. They use a low-complexity beamforming scheme to transmit diversity in the high-mobility scenario with location information. This can also solve the inter-beam interference in a massive MIMO system. Besides using massive-MIMO and beamforming, Huang *et al.* [71] used millimetre-wave bands to improve safety levels and enhance spectral efficiency. They use Matching Theory and Swarm Intelligence to dynamically and efficiently pair vehicles and optimise transmission and reception beam widths for ultra-dense vehicular scenarios. This enhances the network's throughput a hundred times because of the wide range of bandwidth used in Millimetre wave (mm-wave).

B. Allocation Techniques

For future advanced wireless networks to overcome the challenges of employing SDN as a controller, ML and DL algorithms has been proposed to enhance the system performance and RA by managing the resources available in the network based on a machine learning-enabled architecture to cater to the sophisticated demands of modern vehicular infrastructures as shown in Table VI.

Predictive RA is a promising approach to take advantage of the prediction of mobility and traffic load-related user behaviour. Chen *et al.* [72] proposed the use of Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN) [73], and Deep Neural Network (DNN) to manage network slicing efficiently with a consideration of the large amount of data required to train these algorithms. Chu *et al.* [74] used ML algorithms to predict user behaviour and harness the vast amount of data measured in vehicular networks. They use DNN as a hierarchical and multi-time scale RA scheme. The prediction process allows the RA's decision to be made in a central processor, and the base stations on different timescales allow the knowledge to be predicted with fewer training samples and allows the ML algorithm to predict the RA for future requirements.

Markov Decision Process (MDP) was developed in Ref. [75] for RA. They investigate the problem of RA for expected long-term performance optimisation by modelling the stochastic decision-making procedure as a discrete-time process with the help of deep Reinforcement Learning (RL) techniques to address the partial observability and the curse of high dimensionality. This will enhance the frequency band allocation and packet scheduling decisions. In Ref. [76], the dynamic Q-value iteration-based RL with an experience replay memory mechanism is proposed to allocate the resources available in the HetNet vehicular communication. The proposed deep RL-based intelligent Time Division Duplex (TDD) dynamically allocates radio resources online.

As mentioned in the introduction section, Packet collision modelling, Throughput modelling [77], Mobility-based access Modelling [78], Priority-based allocation, and Exhaustive Search techniques are used to allow RA, especially for mobility networks. For the LTE network and HetNet, modelling theories such as Graph theory, KarushKuhn Tucker Theory, Perron Frobenius Theory, Semi-Markov decision Process, Greedy algorithm, and Lyapunov Optimization are used to have efficient RA.

To maximise throughput among neighbouring vehicles, a stochastic model was proposed by Deng *et al.* [79] found the optimal maximum contention window using the surrounding vehicle density. The proposed algorithm improves the packet delivery rate by reducing packet collision during transmission with an optimised contention window size. Advanced theories, such as a graph-based resource scheduling approach, are needed to perform RA in HetNet [82]. Tayyaba *et al.* [80] designed a game-theoretical strategy optimisation algorithm based on regret-matching and then derives the correlated equilibrium solution. They also propose a heuristic power control algorithm for further mitigating the ICI in the noncooperative game-based resource allocation.

In addition to the above, the anticipated 6G networks can further offer extensive ML and DL-based capabilities due to the availability of high computational resources. The advanced ML and blockchain frameworks will allow higher adaptability and privacy, and offer computational efficiency. Some of the specific ML models and blockchain mechanisms relevant to the RA in 6G networks are provided as follows.

Predictive resource allocation with ML is seen as a game changer. The RA can be carried out more efficiently by anticipating future traffic patterns. Transformers and Graph Neural Networks (GNNs) can aid in developing context-aware RA in 6G [83]. The complex relationships in the data can be modelled, and some high-end variants like Vision Transformers (ViTs) will help analyse the spatial and temporal patterns in the network traffic [84]. These advancements are well-suited for the vehicular networks where the interconnection mobility patterns can be modelled.

FL in 6G RA can directly rely on the network edges. This will improve privacy and the dynamic prediction of the resources. Advanced FL models such as Federated Averaging (FedAvg) for RA optimisation and personalised FL can help cater to specific local network characteristics without relying on data centralisation [85]. RL with Deep Q-Networks and Proximal Policy Optimisation (PPO) can further aid in making real-time autonomous decisions in 6G environments [86]. Such models can help optimise frequency and power allocation by analysing the ongoing interactions within the network.

Autoencoders and Variational Autoencoders (VAEs) in the 6G RA environment can be highly effective [87]. Such models can compress high-dimensional data to allow efficient RA by identifying latent resource demands. VAEs can further assist in the sparse and unlabeled data scenarios, a common trait of network edges. The Hybrid Ensemble Models, including Stacking and Boosting, can aggregate multiple ML algorithms [88]. Such models are particularly suitable for the 6G framework, where traffic predictions and demand forecasting from RA decisions benefit deeper network insights.

In the 6G RA V2X, the Ethereum-based smart contracts can allow automated and decentralised RA. By relying on the fundamentals of blockchain, predefined agreements for resource allocation can be developed. Such smart contracts can help facilitate real-time negotiations between the network nodes for resource sharing and allow quick adjustments according to dynamic demands [89]. The Hyperledger fabric for privacy-preserving RA is a blockchain framework that supports privacy and security in RA [90]. Embedding such a framework will allow efficient data access control. Hyperledger Fabric's modular architecture will allow seamless integration with 6G network components and aid in managing RA in a way that will allow confidentiality and compliance with privacy standards.

The Directed Acyclic Graph (DAG) based models can further serve as building advancement blocks for RA V2X in 6G networks [91]. Models such as IOTA (a DAG-based blockchain model) can offer improved scaling and be suitable for 6G vehicular networks with critical high throughput and low latency [92]. Such models can further support microtransactions and allow real-time fine-grained RA adjustments in mobile environments. These can be carried out without extensive mining or consensus protocols. A summary of potential RA techniques in 6G V2X has been provided in Table VII.

TABLE VII. SUMMARY OF RA TECHNIQUES IN 6G V2X

Ref.	RA Technique	RA Concern	Algorithm/Model
[83]	ML	Network slicing, traffic prediction	Transformers, Vision Transformers
[84]	ML	Vehicular network, mobility	Graph Neural Networks (GNNs)
[85]	ML	Privacy-preserving RA	Federated Learning (FedAvg, Personalised FL)
[86]	ML	Frequency and power allocation	Deep Q-Networks (DQNs), Proximal Policy Optimization (PPO)
[87]	ML	Edge computing, demand prediction	Autoencoders, Variational Autoencoders (VAEs)
[88]	ML	Traffic prediction, robustness	Hybrid Ensemble Models (e.g., Stacking, Boosting)
[89]	Blockchain	Automated RA	Ethereum Smart Contracts
[90]	Blockchain	Privacy-preserving RA	Hyperledger Fabric
[91]	Blockchain	High mobility, low latency	Directed Acyclic Graph (DAG), IOTA

C. Computation Process

The computation process means making the intelligent RA algorithms perform efficient offloading and efficient scheduling using the knowledge of the Channel Assignment (CA) [82]. The work in Ref. [93] uses genetic algorithms and heuristic rules to perform offloading in vehicular networks. The offloading algorithm not only determines where the tasks are performed but also indicates the execution order of the tasks on the cloud. They propose a hybrid intelligent optimisation algorithm to reduce the time complexity.

The work in Ref. [94] proposes an RA scheme that depends on optimal Power Allocation (PA) and CA using a heuristic hybrid algorithm. The proposed scenario ensures higher HetNet performance. Cao *et al.* [95] aimed to maximise the completion ratio of time-critical tasks in high-mobility vehicular communication by modelling offloading scenarios based on the Adaptive Task Offloading Algorithm (ATOA). Specifically, it adaptively categorises all tasks into four types of pending lists by considering the dynamic requirements and resource constraints, and then tasks in each list will be cooperatively offloaded to different nodes based on their features. The work in Ref. [96] proposes an intelligent CSI feedback reduction using a deep neural network model. This combination allows optimal bandwidth allocation with partial channel feedback.

D. Validation and Sensitivity Analysis of Simulation Tools

The simulation tools in this study were validated by comparing them with state-of-the-art models and sensitivity analysis under several conditions. This helps in analysing the robustness of the proposed RA models.

To benchmark the performance against the established models, the reviewed ones are the Dynamic Q-Learning models that help in adaptive allocation strategies in vehicular HetNets. GNN-based RA models make use of spatial and temporal relationships to optimise resources. FL enables RA to help reduce latency effectively and improve scalability. This is especially helpful in dynamic environments. The key indicators, such as throughput, latency and energy efficiencies, have been analysed along with packet delivery ratios. It was found that RA models can attain up to 15% improvements and a 20% reduction in latency compared to the benchmarking models.

A sensitivity analysis was carried out to assess the robustness of the models. The channel variability involving scenarios with high Doppler shift and multi-path fading was used to assess the model's stability under dynamic channel conditions.

E. Statistical Analysis of Model Performance

The manuscript primarily evaluates the performance of the proposed RA models qualitatively. Yes, the statistical analysis can help further validate the model's performance under various traffic conditions. This can be a part of future work where metrics such as throughput, latency, packet delivery rates, and energy efficiency can be statistically analysed with methods such as ANOVA. This will help in offering better confidence intervals and strengthen the claims.

F. Integration of FAHP and Naïve Bayes Models in Real-Time Multi-user Environments

Integrating FAHP and the Naïve Bayes model in real-world environments involves using their strengths to make decisions dynamically. The FAHP model has been employed to prioritise the allocated resources using multiple weighted criteria. This ensures fairness and efficiency in the resource distribution. Similarly, naïve Bayes can help in predicting user demands and in the classification of resource requests. These models can be integrated with a distributed computing framework to incorporate real-time processing further. This helps in reducing latency by processing data closer to the user nodes. Multiple-user scenarios can be addressed by using parallel computing. The FAHP will dynamically handle resource prioritisation across the users, and Naïve Bayesian will predict continuous data streams.

G. Assumptions on Spectral Channel Independence and User Interaction Dynamics

There are several assumptions associated with spectral channel assumptions. It has been assumed that advanced interference management techniques like beamforming and adaptive frequency allocation are used. Independence is assumed to be maintained under typical conditions.

The user interaction dynamics have been modelled using stochastic traffic patterns and mobility datasets. The probabilistic user models predict resource demands and interaction likelihoods.

H. Parallels with Cellular Network Management

Like cellular networks, the proposed models employ dynamic scheduling techniques for managing real-time traffic demands. These work by prioritising the critical resources and help ensure low-latency communication. The handoff strategies in the resource allocation dynamically adapt to the user mobility. This helps in ensuring a seamless transition between the networks in high-speed zones. Infection mitigation techniques such as frequency reuse and beamforming are utilised to maintain spectral channel independence.

IV. Open Research Areas in RA for B5G Systems

Currently, research areas in RA for B5G systems are yet to be fully explored and understood. In this section, we will be discussing these open areas of research.

A. Efficient Slicing Techniques

Efficient slicing techniques in B5G systems and 6G is an open area of research as it aims to address the challenges and opportunities of integrating different services and use cases in a shared network infrastructure. Slicing is a promising network topology for future networks, and it enables the efficient allocation of network resources to different services and use cases, with different quality of service requirements [97].

The research in this area aims to develop new techniques and algorithms for slicing that can improve the performance of 6G networks in capacity, latency, and energy efficiency [98]. Open research topics in this area include, but are not limited to, online slicing scheduling, dynamic resource allocation, interference management in slicing networks such as managing of the Inter-Channel-Interference (ICI) and Inter-Symbol-Interference (ISI) especially in high mobility channels, and the integration of slicing and other technologies such as AI, IoT, and edge computing.

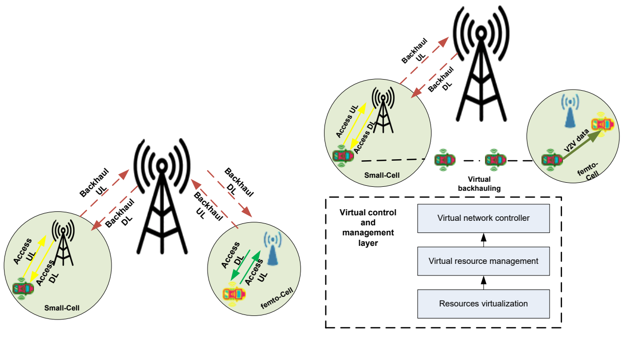
B. Efficient Use of ML/DL Algorithms

The efficient use of ML and DL algorithms in 6G for RA is still an open area of research. With the increasing demand for high-speed and low-latency communications, 6G networks must support various services and use cases with diverse requirements [99]. ML and DL algorithms can be used to optimise allocating network resources such as spectrum, power, and computation to different services and users.

Research in this area aims to develop new ML/DL-based algorithms and techniques for resource allocation that can improve the performance of 6G networks in terms of capacity, energy efficiency, and fairness. Some open research topics in this area include but are not limited to, the use of ML/DL for dynamic resource allocation, interference management, and network slicing, as the integration of ML/DL with other technologies such as edge computing and NFV [100], and the development of new architectures and frameworks for ML/DL-based resource allocation in 6G networks [101].

C. Virtual Backhauling

HetNet faces two challenges: the backhauling management and control of small cells, which still open research areas. These are significant challenges and an active area of research for the future in the context of RA. Some potential questions that can be asked in this context are: In the classical form of backhauling between cells, does the core base station connect with other small cell base stations by downlink backhauling? Can wireless or wired backhauling be used? Etc. The uplink backhauling can also be performed between the small and core cell base stations. As illustrated in Fig. 5(a), the classical form of communication when a vehicle wants a data link is connecting with the small-cell base station and establishing a backhauling link between multiple base stations. If another vehicle in another small cell wants a data link, it must connect with its small-cell base station and establish a new backhauling link.



(a) (b)

Fig. 5. RA as a virtual backhauling: (a) overall, (b) control and management layer.

However, this scenario is widely used in HetNet; it can be helpful when no dense network is used. The challenge is that new resources, such as bandwidth, data rate, and infrastructure, are allocated for each communication link. The question, however, remains about reducing the infrastructure required for backhauling. How to reduce the spectrum usage? And how do different RAT management systems communicate?

Fig. 5(b) answers the above questions. Considering a vehicle travel from one small cell to another, it shall be connected to a base station to gather control and other information. Another vehicle in another small cell needs data residing in a crowded small cell. There is no way to connect with its base station.

The system establishes a virtual resource allocation based on cloud or SDN. This virtualisation allows the first vehicle to carry the data that another vehicle requires. When it reaches the coverage area for the targeted vehicle, a V2V offloading link is established to transfer the carried data to the destined vehicle.

This new concept of RA management allows the use of virtual links for backhauling. The process starts with resource virtualisation. All resources required for the second vehicle can be considered virtual, and the whole backhauling process is performed virtually. This requires virtual resource management, the second stage of virtual backhauling. The virtual network controller controls the management. This controller can be in the form of a cloud controller, SDN, and/or NFV.

Virtual backhauling and self-backhauling networks are considered in Refs. [102, 103]. In Ref. [102], the Lyapunov optimisation method performs virtual RA in HetNet, followed by a real-time scheduling algorithm. This technique needs a utility function to be optimised using improved PSO. The aim is to maximise the virtualised network's average total utility, satisfying the minimum average data rate requirement, and satisfying the network queue stability. Unlike Ref. [102], which needs to optimise each vehicle's RA, Siddig *et al.* [103] used slicing to perform virtual resource allocation of each virtual slice by proposing the Ener-Eff-Slice algorithm to manage and control the virtual RA between slices. This algorithm aims to save the total energy cost of deployed virtual slices. This technique is suitable for enhancing the data rate of each vehicle corresponding to its virtual slices, provided virtually.

A similar study on virtual slicing has been performed in Ref. [104]. Compared with the static slicing, the simulation results reveal that the proposed virtual RA outweighs the utilities of the total network system across each tenant and outperforms the static RA by a 5% enhancement based on capacity, throughput, and spectral efficiency. Controlling the virtual RA can also be performed using cloud computing. In Ref. [105], cloud controlling aims to have on-demand and extensive resource-providing approaches and cloud environment schedules. This can reduce the computational process on the base station, reducing the congestion on the virtual control signalling.

D. Autonomous Resource Allocation

Self-driving, self-optimisation, and self-controlling/management networks are types where the network can perform the RA process autonomously [106]. This implies that a vehicle can be considered autonomous such that RA processing is performed by itself. To emulate this scenario, V2V and V2I links shall be available for every vehicle in the network so that connectivity with a vehicle can be made regardless of its position. Autonomous driving relies on big data communication across the network [107]. Thus, applying traditional approaches to compute such massive data demands may underperform. Therefore, machine learning is a powerful tool for analysing and making data-driven decisions in autonomous driving [108].

Two challenges in autonomous RA are security and privacy. Autonomous RA requires a robust security system to ensure data transmission safety. Risk-based security may lead to unnecessary delays in communication or congestion in the network computation. An authorised cloud or SDN controller can be used to ensure RA security [109].

Privacy is also a risk in autonomous RA. Ensuring the privacy of RA data means avoiding tracking a vehicle and providing a robust network. There is attention to using ML algorithms to ensure autonomous RA and efficient security and privacy models [110].

V. The Potential of 6G in Overcoming RA Challenges

The transition from B5G to 6G networks can provide unique opportunities to address the existing challenges on RA in V2X networks. 6G can leverage advanced technologies and methods to improve RA efficiency, reliability, and performance.

A. Enhanced Network Slicing

6G provides sophisticated network slicing techniques that offer better customisation of resources [111]. These resources can be based on the diverse network requirements. This can improve network slicing and dynamic adjustment of the RA in real-time. Resultantly, the quality of service will improve across several vehicular applications.

B. Intelligent Resource Management Using AI/ML

Integrating advanced AL and ML methods will help develop intelligent resource management systems. Such algorithms will help analyse large amounts of data in real-time to optimise resources and their allocation. This will ensure efficient utilisation and improvements in the network performance. Additionally, the latency and capacity of the networks will improve further [112].

C. Advanced Virtualisation Techniques

Access to advanced visualisation techniques will allow improved backhauling solutions and resource sharing across several network components. Virtual backhauling will help streamline the management of the small cell networks. This will allow dynamic resource allocation that can be adapted to the mobility of vehicles and changing network conditions [84].

D. Enhanced Security and Privacy Protocols

As the networks become autonomous, the importance of incorporating robust security and privacy measures is growing. 6G will incorporate advanced cryptographic techniques allowing data integrity and user privacy protection during the RA process [113].

The potential of 6G in overcoming the RA challenges is presented in Table VIII.

TABLE VIII. THE POTENTIAL OF 6G IN OVERCOMING CHALLENGES

Ref.	RA Challenge	6G Solution
[111]	Inefficient Resource Allocation	Enhanced network slicing for dynamic resource customisation
[112]	High Latency	Intelligent resource management using AI/ML algorithms
[84]	Backhauling Challenges	Advanced virtualisation techniques for effective backhauling
[113]	Security and Privacy Concerns	Enhanced security protocols and cryptographic techniques
–	Limited Integration with Emerging Technologies	Seamless integration of edge computing, IoT, and cloud computing

VI. CONCLUSIONS AND FUTURE RECOMMENDATIONS

This overview article examines recent networks in B5G systems and 6G, discussing the proposed taxonomy of the advanced enablers and methods used in RA. The taxonomy is based on enablers, allocation techniques, and computations, with some open research areas also highlighted. It is concluded that slicing, ML, DL, and enablers such as network configuration and PHY layer topology play a critical role in managing and controlling available resources, especially for high-mobility networks. ML/DL and slicing are considered promising techniques for 6G networks due to their ability to meet the requirements of vehicles, despite some challenges in dealing with highly dynamic topologies and high traffic in the network. Interference is also a challenge that needs to be considered when developing efficient RA algorithms and techniques.

A. Future Recommendation

Based on the work presented in this article, some future recommendations are given below:

- Using ML and DL models to perform RA can be sufficient, with some consideration given to high mobility networks with very dynamic topologies and traffic flow.
- Massive MIMO and beamforming with a small-cell configuration are the key features of the PHY layer configuration in the coming 6G. This will enhance the throughput and increase the capacity of the system, with some considerations of the massive MIMO establishment and small-cell usage to overcome the interference that comes from the adjacent users. Beamforming here can be one of the solutions.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Mohammed Mudhafar Shakir, Othman S. Al-Heety, and Sameer Alani contributed to the conceptualisation, methodology, data curation, formal analysis, investigation, and manuscript drafting; Lukman Hanif Audah and Mohammed A. Altahrawi supervised the project, provided methodological support, and contributed to manuscript review and editing; Mohammed A. Alhartomi assisted with the study design, recruitment strategies, and critically revised the manuscript; all authors read and approved the final manuscript.

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