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# Optimizing V2X Communications for 6G: A Summary of Techniques and AI Methods



Ali Belgacem and Abbas Bradai

**Abstract** This summary research paper provides a comprehensive overview of Vehicle-to-Everything (V2X) communications, including various communication types and the roles of base stations. It covers resource allocation techniques and beamforming for high-quality connectivity and addresses energy efficiency optimization metrics. The paper also discusses artificial intelligence methods and their integration to optimize these systems and enhance performance. This research serves as a valuable guide for those aiming to contribute to advancements in 6G technologies for efficient vehicular communications.

**Keywords** 6G · Vehicle to everything (V2X) · Artificial intelligence (AI) · Resource allocation · Beamforming · Base station · Energy efficiency

## 1 Introduction

6G is significantly ahead of 5G by using the terahertz, millimeter wave and sub-6GHz bands, along with satellite integration and access to dynamic spectrum for improved connectivity. By focusing on artificial intelligence, 6G technology aims to improve network operations, decision-making, and user experiences while saving more energy [1]. However, the transition to 6G may increase communications complexities and power requirements, especially regarding continuous connectivity in V2X cellular technology, requiring efficient power management, especially with the advent of electric vehicles. As such, key technologies such as Orthogonal Frequency Division Multiple Access (OFDMA) and the 3rd Generation Partnership

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Project (3GPP) will enhance global interoperability and integrate new innovations, propelling 6G networks toward superior performance and capabilities [2].

The integration of resource allocation and AI-based methods is essential for enhancing the efficiency and effectiveness of V2X communication systems. By optimizing resource utilization and energy consumption, AI-driven approaches can significantly improve the reliability, scalability, and sustainability of V2X networks, paving the way for safer and more efficient transportation systems of the future. On the other hand, joint beamforming involves coordinating beamforming techniques for transmission and reception among multiple vehicles and base stations. This leads to enhanced reliability, coverage, and throughput while minimizing interference and energy consumption, thereby contributing to the overall effectiveness of V2X communication networks [3].

Existing surveys in V2X communication have explored resource allocation [4], beamforming [5], and energy consumption [6]. However, these topics are often studied separately, lacking research on their complex relationships. Additionally, recent advancements in deep reinforcement learning and other methodologies are not adequately represented in existing works, hindering a comprehensive understanding of energy efficiency optimization in V2X systems. To address this gap, more rigorous analysis and consideration of real-world scenarios are needed. The main contribution of this research is to provide a comprehensive summary by combining three research trends in the context of V2X: artificial intelligence, resource allocation, and beamforming, with a focus on efficient base station energy consumption. By synthesizing current research, identifying challenges, and proposing future directions, this paper serves as a valuable resource for researchers and practitioners in V2X communication.

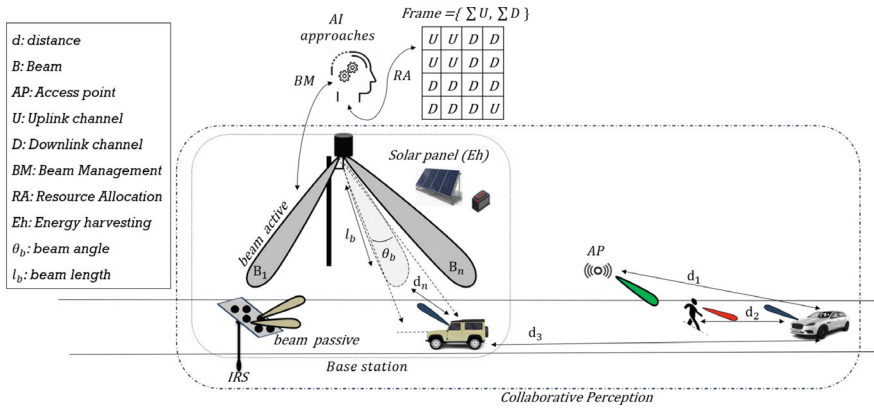
The remainder of the paper is organized as follows: Sect. 2 covers the basics of V2X communication. Sections 3, 4, and 5 provide a literature summary on resource allocation, beamforming, and energy efficiency, respectively. Section 6 discusses AI method applications in V2X networks. Following this, Sect. 7 presents challenges and future directions of the studied field. Finally, Sect. 8 concludes the paper.

## 2 The Basics of V2X Communication

Overall, V2X connectivity holds great potential to enhance traffic flow and enable innovative transportation services in both urban and rural areas (Fig. 1). Here are the basics of V2X communication.

### 2.1 V2X Communication Types

V2X communication projects aim to provide intelligent vehicle communication, covering various aspects such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure



**Fig. 1** V2X Resource allocation and beamforming with AI

(V2I), Vehicle-to-Pedestrian (V2P), Vehicle-to-Device (V2D), Vehicle-to-Grid (V2G), and Vehicle-to-Network (V2N). This communication ensures safety in autonomous driving by enabling vehicles to be aware of their surroundings and other road users through Collaborative Perception (CP) technology, which allows interaction between multiple entities near vehicles. With the upcoming 6G technology, V2X communication relies on Dedicated Short Range Communications (DSRC) and cellular networks, particularly utilizing mmWave channel propagation [3]. Therefore, cellular V2X (C-V2X) emerges as a crucial type within this context [7].

## 2.2 Base Station Functions

In V2X networks, the Medium Access Control (MAC) layer of base stations performs critical functions and requires specific power requirements [8]. Here's an overview of the main of them:

- **Manage channel access:** Modern 6G base stations are expected to use orthogonal frequency division multiplexing (OFDM) as a critical technology to access V2X networks. This enables high data rates, reliable communications, and efficient use of the radio spectrum [9].
- **Frame Structure Management:** The base station defines the structure of communication frames, incorporating synchronization headers, data payload, error checking, and acknowledgment mechanisms to ensure that transmitted data is organized into coherent frames for efficient transmission and reception [10].
- **Transmit and receive signals:** The base station contributes to energy consumption through the transmission and reception of radio signals, crucial for facilitating communication between vehicles [8]. Transmitting data frames at higher power levels and receiving acknowledgment signals are particularly energy-intensive, especially in scenarios with dense traffic or extended communication ranges.

### 3 Resource Allocation Techniques

In resource allocation for V2X networks, three primary resources are crucial: power, channel, and spectrum resources. They are mentioned in [4, 11]. Resources are optimized in various ways, among them:

*Dynamic Resource Allocation* Adaptive power control, spectrum management, and Time Division Multiple Access (TDMA) are crucial techniques for optimizing energy efficiency and communication reliability. Base stations dynamically adjust transmission power levels based on distance and signal quality, conserving energy by reducing power for nearby vehicles while maintaining reliable communication [12]. Spectrum management ensures efficient allocation of frequency bands, minimizing interference and maximizing spectrum utilization through techniques like spectrum sensing and cognitive radio.

*Traffic-Aware Scheduling* Base stations implement several strategies to enhance energy efficiency and prioritize safety-critical traffic. Firstly, prioritization of safety-critical messages ensures timely delivery of collision warnings and emergency alerts over non-critical traffic, reducing the need for retransmissions and conserving energy. Additionally, dynamic bandwidth allocation allows base stations to adaptively allocate bandwidth to V2X applications based on their quality of service requirements and traffic loads [13]. During low-traffic periods, base stations can allocate unused bandwidth to energy-efficient modes or reduce the number of active transmission antennas, further optimizing energy consumption within the network.

*Cooperative Communication* In V2X systems, base stations employ relay-based and group-based communication techniques to enhance energy efficiency and extend communication capabilities. Relay-based communication involves nearby vehicles acting as relay nodes, extending the communication range and reducing the transmission power required for direct communication between distant vehicles. By strategically leveraging relay nodes, base stations can achieve significant energy savings while maintaining reliable communication. Additionally, group-based communication organizes V2X devices into communication groups based on proximity or traffic patterns. This approach enables base stations to transmit data simultaneously to multiple vehicles within the same group, reducing overall energy consumption compared to individual point-to-point transmissions and improving network efficiency [7].

*Joint resource allocation and beamforming optimization* Intelligent Reflecting Surface (IRS) technology significantly enhances spectral and energy efficiency in Vehicle-to-Everything (V2X) communication by improving beamforming and resource allocation. IRS optimizes beamforming by dynamically adjusting reflection coefficients, leading to higher signal gains. Integrating IRS into resource allocation involves optimizing and managing channel access, resulting in improved overall performance [14].

## 4 Beamforming

Beamforming is essential in modern V2X communication for enhancing performance and efficiency by enabling directional signal transmission and reception. Several beam types have been addressed in the literature, as mentioned below:

- **Narrow beam:** It refers to the use of directional antennas to focus the transmission and reception of signals into a narrow, targeted beam rather than broadcasting signals in all directions, as detailed in paper [15].
- **Passive beam:** Passive beamforming involves the design and arrangement of antennas to naturally direct signals in specific directions. This is achieved using fixed antenna arrays, reflectors, and lens antennas [2]. The physical shape and orientation of the antenna elements cause the signals to combine constructively in targeted directions, enhancing signal strength without the need for electronic adjustments.
- **Active beam:** This type uses electronically controlled antennas to dynamically direct signal beams, improving connectivity, reducing interference, and improving signal quality [8]. The researchers in [2] suggested a combination of active and passive beamforming techniques to significantly enhance communication throughput and reliability. Active beamforming dynamically steers the signal to adapt to changing conditions, while passive beamforming optimizes signal directionality through fixed antenna configurations.

Effective energy consumption requires different management strategies for various types of beams, as illustrated below:

- **Beam selection:** Dynamic beamforming strategies can achieve reliable communication while minimizing energy consumption, but the selection process must balance connectivity needs with energy demands [16]. Energy-efficient algorithms aim to maximize communication quality while minimizing energy expended on beamforming, enhancing V2X network sustainability and effectiveness. Factors like vehicle density, mobility patterns, channel conditions, and traffic dynamics influence beam selection.
- **Beam tracking:** Beam tracking is the dynamic adjustment of wireless communication beams between vehicles and surrounding infrastructure to optimize signal strength and minimize energy consumption. Adjusting beamforming parameters in response to changing environmental conditions, reduces unnecessary energy usage associated with maintaining connections. However, it is essential to take into account the channel state information (CSI) for effective beam tracking [5].
- **Beam alignment:** It refers to the process of precisely aligning directional antennas between vehicles and roadside infrastructure to establish and maintain reliable communication links while minimizing energy usage. The alignment of the beam is influenced by factors such as the size of the beamwidth and the quality of the channel state information [8].
- **Beam recovery:** It refers to the process of regaining or reestablishing a communication beam after a disruption or interruption. This method of beam management

enables the detection of potential link failures and the identification of alternative beam pairs for mmWave communication. Thus, it is necessary to minimize the impact of blockage and the duration of link failure [17].

- **Beam switching:** It involves transitioning between different communication beams to sustain connectivity and optimize communication performance, all while minimizing unnecessary energy consumption. This process utilizes predictions of a vehicle's next position to facilitate smooth transitions to upcoming beams. Notably, larger beam widths result in fewer instances of beam switching [8].
- **Beam training:** It refers to the process of optimizing beamforming parameters (beam direction, width, and power) to establish efficient communication links between vehicles and base stations [5, 8].

## 5 Energy Efficiency in V2X Communications

The following optimization metrics ensure effective energy use, often resulting in reduced energy consumption. They include:

- **Interference:** Interference optimization for energy efficiency for V2X networks can be achieved in various ways: Interference prediction, interference minimization, multiple access interference, and interference mitigation, as shown in [18], respectively. Generally, interference improvement relies on maximizing the signal-to-noise ratio (SNR).
- **Offloading:** It involves shifting computational and data processing tasks from vehicles to external infrastructure, such as roadside units or cloud servers. This approach can reduce the computational burden on vehicles, enhance network resource utilization, and employ intelligent strategies for dynamic task allocation and efficient data management [19].
- **Throughput:** Throughput measures the data transmitted between source and destination within a timeframe, often in bits per second (bps). Effective throughput accounts for overhead, retransmissions, and protocol inefficiencies, representing the actual data rate achieved. For example, reference [20] proposes maximizing total throughput in NR-V2X networks across subcarriers while considering available power and minimum transmission rate constraints.
- **Energy Harvesting Efficiency:** Energy harvesting involves converting ambient energy sources like solar, kinetic, or electromagnetic energy into usable electrical power to support V2X communication systems. Improving energy harvesting efficiency is crucial for extending the operational lifespan of V2X devices, reducing dependence on traditional power sources, and promoting sustainability. In reference [21], researchers utilized energy harvesting to achieve long-term energy efficiency maximization by employing power splitting to delicately divide the harvested energy.

**Fig. 2** Percentage of energy efficiency metric optimization usage

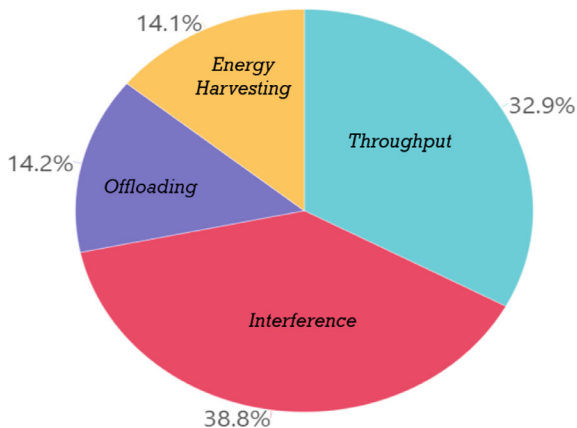


Fig. 2 shows the percentage use of the different improvement metrics mentioned above from 2020 to mid-2024 (according to Google Scholar).

## 6 Utilized AI Approaches

Most investigations into the issue studied in this paper classify it as a non-convex problem [22]. Thus, by employing the AI approaches, V2X networks can achieve more efficient and intelligent beam management and resource allocation, leading to improved communication performance and energy efficiency. In recent years, researchers have begun applying various types of AI methods to this research trend [23]. According to our statistics from Google Scholar for the period from 2020 to mid-2024 (Fig. 3), it is notable that deep reinforcement learning is used by a significant portion of the scientific research community, and advanced reinforcement learning techniques are emerging as new propositions. These are promising solutions. Therefore, we focused our classification on these latter types.

### 6.1 Deep Reinforcement Learning (RL)

The most commonly utilized methods in the literature are as follows:

*Deep Q-Learning (DQL)* It combines the strengths of reinforcement learning with the powerful symbolic capabilities of deep neural networks, enabling efficient handling of high-dimensional state spaces, learning directly from initial inputs, generalization across states, scaling to complex environments, improving policy learning, dealing with partial observability, and integration with other deep learning techniques [24, 25]. In [26], Deep Q-Learning optimizes joint beamforming by effectively handling complexity and adapting to changing conditions. This ensures optimal

performance and can effectively mitigate blocking effects. DQL maximizes the total communication rate of target vehicles while also ensuring the service quality of each target vehicle.

*Multi-Agent RL (MARL)* It possesses the capability to capture complex interactions, emergent coordination, division of labor, adaptability to dynamic environments, learning from others, robustness to failures, privacy preservation, and real-world applicability. For example, in [27], it is utilized in various V2I and V2V scenarios within C-V2X cellular communications to improve the joint optimization of the spectrum and power allocation.

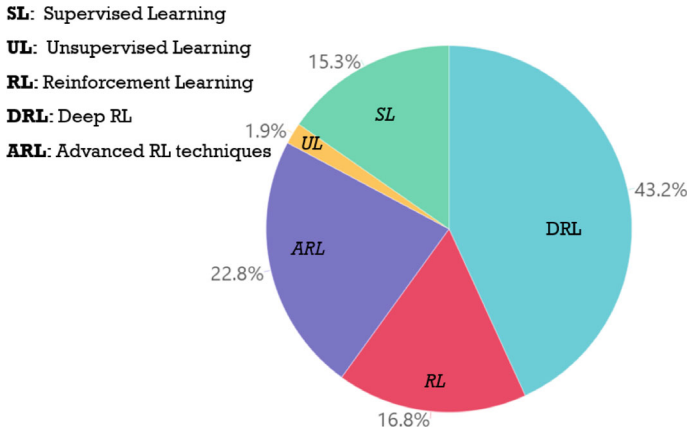
*Proximal Policy Optimization (PPO)* PPO's stability in training neural network policies makes it advantageous for optimizing beamforming strategies in wireless communication systems. In the study [22], the authors utilize the PPO algorithm to obtain the optimal solution to the formulated problem in the context of RIS-assisted 6G-V2X communication networks. By iteratively adjusting policy parameters and leveraging the clipping surrogate method, the algorithm effectively improves network performance.

*Multi-armed bandits (MAB)* Within beamforming systems, MAB algorithms dynamically select optimal beams or combinations, considering channel conditions, traffic demands, and interference levels, thus improving communication performance and spectral efficiency. The methodology presented in reference [28] employs Contextual Bandit to manage interference while allocating mmWave beams for vehicle service in the network. By leveraging neighboring beam status knowledge, it identifies and avoids potential interfering transmissions, ensuring minimal interference even under heavy traffic loads.

## 6.2 Advanced RL Techniques

The utilization of advanced RL techniques is still in its early stages in this studied field, with the widespread adoption of federated methods being prominent among various approaches.

*Federated Learning (FL)* substantially benefits V2X communication and base stations within wireless networks. It allows for distributed optimization and resilience to network failures in base stations, improving scalability, strength, and resource access. In V2X communication, FL supports localized learning and collaborative decision-making among vehicles, improving communication reliability and efficiency. Additionally, FL reduces energy consumption through energy-efficient training and adaptive model updates, promoting sustainability in wireless network operations. The article [29] presents a task offloading and resource allocation algorithm for connected and autonomous vehicle networks, using Federated Reinforcement Learning (FRL). This method, within a cooperation architecture among vehicles, roads, and base stations, aims to reduce task execution delays under different constraints. It



**Fig. 3** Percentage of primary AI methods used for energy efficiency

boosts system throughput by optimizing task offloading and resource allocation, cutting down on data transmission delays and communication overhead, and adapting to changing network setups.

### 6.3 Integrating AI Approaches in V2X Networks

Implementing Deep Reinforcement Learning involves five main steps, as follows:

*Data Collection and Preprocessing* AI models require extensive data from V2X networks, including vehicle mobility patterns, channel conditions, and network usage statistics. Effective data collection and preprocessing are crucial for accurate model training [28, 29].

*Making of the Markov Decision Process (MDP)* It is one of the most fundamental components in a reinforcement learning (RL) problem. Typically in V2X scenarios, the base station or vehicle is considered the agent, which is the learner interacting with the environment by taking different actions in various states [25].

*Deep learning Network Model* This refers to the network architecture (layers, nodes, pipelines) adopted to construct our deep AI model. Various architectures are utilized, including Neural Networks (NNs), Support Vector Machines (SVMs), and others [24, 25].

*Model Training and Deployment* Trained models can be deployed at base stations for real-time decision-making. Continuous learning and model updating are essential to adapt to evolving network conditions and vehicular environments.

*Performance Evaluation* The effectiveness of AI models should be evaluated using metrics such as latency, throughput, energy efficiency, and overall network performance. Real-world trials and simulations help in fine-tuning the models for optimal performance.

#### **6.4 *Difficulty in Integrating AI Approaches***

Integrating AI into V2X-6G systems presents several challenges. One key issue is communication overhead, as frequent updates between vehicles and base stations demand low-latency connections and efficient handling of network congestion and mobility. The diversity of vehicle data complicates model training, while privacy and security risks, such as model poisoning, add further complexity. High-speed environments impose resource constraints that hinder efficient model training. As the vehicle count increases, scalability becomes a problem, complicating update management and model convergence. Compatibility with legacy systems, growing computational demands, and real-time decision-making are also critical challenges.

### **7 Challenges and Future Directions**

Some key research areas poised to expand the capacity of wireless access for V2X communications include advanced modulation and massive multiple access techniques such as mmWave frequency bands, massive MIMO communications, Orthogonal Time-Frequency Space (OTFS) modulation, and Non-Orthogonal Multiple Access (NOMA) [3, 30]. Additionally, computation and network management at scale through mobile edge computing (MEC) and vehicular cloud and fog computing are critical areas of focus [30].

Collaborative efforts and the integration of emerging technologies are essential to proposing modern solutions that address current challenges such as mobility management, interference management, channel estimation, and efficient network slicing [4]. In terms of AI opportunities, the availability and training of datasets, as well as the consideration of performance parameters and computational complexity, are crucial for creating effective and credible models [31]. These advancements will include the allocation of V2X network resources and beam management for efficient power transfer. They will also involve exploring energy harvesting and renewable energy integration to support sustainable V2X ecosystems. Research should focus on developing adaptive algorithms to manage dynamic changes in V2X environments, exploring hybrid approaches that combine AI and traditional methods, and investigating the scalability of these solutions in larger, more complex networks for practical deployment.

On the other hand, while effective in simulations, the proposed methods face challenges in real-world V2X environments, including dynamic traffic, interference,

hardware limitations, latency, and network congestion. Future research should prioritize field tests and pilot studies to evaluate the practical viability of these methods in live V2X scenarios

## 8 Conclusion

In this paper, we addressed the current state-of-the-art in improving resource allocation and beamforming in 6G-V2X networks, leveraging artificial intelligence techniques to enhance energy efficiency in base stations. We provided a summary of important research in this direction. The integration of AI to improve resource allocation and beamforming in 6G-V2X networks shows great potential for creating energy-efficient base stations. This combination not only enhances vehicular communication performance but also aligns with the broader goal of developing sustainable and efficient next-generation networks. To the best of our knowledge, this is the first study examining the combination of resource allocation, beamforming, and artificial intelligence in V2X networks.

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