The State of AI-Empowered Backscatter Communications: A Comprehensive Survey

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Abstract

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We begin with an introduction to BC and an overview of the AI algorithms employed in BC. Then, we delve into the recent advances in AI-based BC, covering key areas such as backscatter signal detection, channel estimation, and jammer control to ensure security, mitigate interference, and improve throughput and latency. We also explore the exciting frontiers of AI in BC using B5G/6G technologies, including backscatter-assisted relay and cognitive communication networks, backscatter-assisted MEC networks, and BC with RIS, UAV, and vehicular networks. Finally, we highlight the challenges and present new research opportunities in AI-powered BC. This survey provides a comprehensive overview of the potential of AI-powered BC and its insightful impact on the future of IoT.

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***Abstract*—The Internet of Things (IoT) is undergoing significant advancements, driven by the emergence of Backscatter Communication (BC) and Artificial Intelligence (AI). BC is an energy-saving and cost-effective communication method where passive backscatter devices communicate by modulating ambient Radio-Frequency (RF) carriers. AI has the potential to transform our way of communicating and interacting and represents a powerful tool for enabling the next generation of IoT devices and networks. By integrating AI with BC, we can create new opportunities for energy-efficient and low-cost communication and open the door to a range of innovative applications that were previously not possible. This paper brings these two technologies together to investigate the current state of AI-powered BC. We begin with an introduction to BC and an overview of the AI algorithms employed in BC. Then, we delve into the recent advances in AI-based BC, covering key areas such as backscatter signal detection, channel estimation, and jammer control to ensure security, mitigate interference, and improve throughput and latency. We also explore the exciting frontiers of AI in BC using B5G/6G technologies, including backscatter-assisted relay and cognitive communication networks, backscatter-assisted MEC networks, and BC with RIS, UAV, and vehicular networks. Finally, we highlight the challenges and present new research opportunities in AI-powered BC. This survey provides a comprehensive overview of the potential of AI-powered BC and its insightful impact on the future of IoT.**

***Index Terms*—Backscattering communication, ambient backscattering, wireless powered communication, AI, machine learning, RL, DRL, and 6G.**

I. INTRODUCTION

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As we move towards a more connected future, the deployment of billions of devices in B5G/6G networks represents a significant opportunity to advance ultra-low power wireless communication [1], [2]. Furthermore, the Internet of Things (IoT), poised to be one of the key technologies in the 6G era, will provide the necessary infrastructure to seamlessly connect an unprecedented number of low-power, sensor-like devices with data sensing and transmission capabilities, bringing to life a multitude of new applications [3]. In this future vision, high-density heterogeneous devices needing high throughput, ultra-low latency, and AI-powered decision-making will be the norm. However, powering these billions of devices is a formidable challenge, especially when battery maintenance is impossible due to the cost, inconvenience, or network size involved [4].

Given the powering challenge of billions of devices, Backscattering Communication (BC) technology becomes an attractive alternative, providing a cost and energy-efficient solution that enables passive devices to communicate by modulating ambient Radio-Frequency (RF) signals, eliminating the need for complex circuitry, power-hungry active components and reducing power consumption to the bare minimum [5], [6]. Backscattering technology was first used in World War II to distinguish enemy fighter planes, and subsequently, backscatter-related Radio Frequency Identification (RFID) products emerged and focused on commodity identification and supply, then used in electronic toll collection extensively [7], [8]. In a BC system, a backscattering device uses an antenna to reflect and modulate the incoming RF signal. This antenna is typically a passive device, meaning it does not require its power source. Instead, the backscattering device modulates its signal by modulating the antenna's reflection coefficient, which determines how much of the incoming signal is reflected. One common technique is to use a switch or diode to change the antenna's electrical length, which changes the phase of the reflected signal. The backscattering device can transmit information by modulating the reflected signal phase. BC offers several advantages that make it a promising alternative to traditional wireless communication technologies in certain applications.

BC is making its mark in the world of low-power communication, as devices exchange data without being tied to a power source. This remarkable feat is achieved by modulating ambient RF signals, delivering a creative and energy-efficient solution. However, the road ahead for BC technology has its challenges [9], [10]. The complex nature of RF signals, with their varying strengths and frequencies, presents obstacles to reliable and accurate BC communication. Furthermore, limited data rate and transmission range are ongoing hurdles to overcome, apart from interference and security issues. Despite these obstacles, the demand for BC technology continues to grow, driving the need for more efficient and scalable solutions [11], [12].

Nevertheless, BC remains a promising technology in the world of low-power communication. With its innovative approach, BC is paving the way for a more connected and sustainable future. As BC technology continues to evolve, we can expect to see more breakthroughs and solutions to the challenges that lie ahead. This is where Artificial Intelligence (AI) comes in, as it rapidly changes the technological landscape of wireless communication networks. From the IoT to Industry 5.0, AI is revolutionizing how we interact with technology. With the advent of 6G wireless networks, AI is set to take communication to the next level, as highlighted in [13], [14]. AI's ability to analyze vast amounts of data in real-time and make intelligent decisions has been instrumental in improving the efficiency and performance of wireless networks. Its integration with big data analytics allows real-time network status monitoring and predictions, resulting in a more adaptable and reliable communication infrastructure, as noted in [15], [16]. While BC technology has already seen benefits in the IoT, with its energy-efficient and cost-effective approach to communication proving to be an attractive solution for battery-free and low-power devices, the intelligence aspect of BC systems is still in its infancy. The potential for improvement is vast, as discussed in [17], [18]. AI can be utilized to solve the challenges that BC systems face, such as poor signal detection and channel estimation, and to mitigate the impact of jamming/interference while ensuring security. Its implementation in BC systems will also lead to decreased delay and increased throughput, making it a crucial component for the future of BC. AI-based backscatter-assisted networks, such as relay, cognitive, and MEC networks, have the potential to revolutionize communication. Its integration with RIS, UAV, and vehicle networks will bring about a new era of communication that is more connected, efficient, and intelligent, as highlighted in [15], [19].

A. Motivation for this Survey

Since the last decade, a speedy development in BC has been noticed and several surveys have been published. However, there is still a need to provide an organized and comprehensive article on AI-based solutions to the challenges and integration of B5G/6G technologies in backscattering communication. This article aims to provide a complete AI-based solution and a detailed overview of AI algorithms. These AI-based solutions deal with the challenges while applying the backscattering to practical systems and integrating with B5G/6G technologies. The article [20] reviews BC and its practical applications, including encoding and data extraction, communication modes, modulation schemes, and multiple access techniques. It also discusses data and power transfer schemes, reliability, security, and range extension and highlights BC applications, research challenges, and future directions. In contrast with our survey paper, [21] provided a thorough overview of backscatter communications, including its historical development, fundamental principles, and challenges. The survey also distinguishes monostatic and bistatic backscatter and compares them. However, it does not touch on the role of AI in the BC system, which is the focus of this paper. Similarly, the work in [22] emphasized the significance of backscattering in IoT, covering the advances in the field of BC, including its working principles, network architecture, applications, and techniques. However, this paper does not address the role of AI in BC, its algorithms, or the benefits it offers. As a result, it lacks AI-based solutions to the challenges in BC.

In another survey [23], the authors provided an overview of backscattering systems, specifically those with passive receivers, which form the basis for Backscattering Tag-to-Tag Networks (BTTNs). BTTNs allow tiny, batteryless RF tags to communicate and perform RF-based sensing without needing a battery. The paper discussed the recent innovations in hardware design, energy harvesting, and the challenges in scaling up the architecture to a network. It also highlighted the potential applications and future research directions in the field. In another survey, the authors in [24] described the utilization of the backscattering along with the non-coherent technique. Using the two techniques, the authors proposed the 6G framework to achieve the desired properties like optimal energy and spectral efficiency besides low hardware cost. This paper presented an enabling framework for 6G networks. Moreover, the integration of non-coherent and backscattering with many technologies was discussed. The joint scope of non-coherent and backscattering with other emerging 6G technologies is also identified. In the end, the detailed applications and uses of said technologies were discussed.

In [25], the authors provided a comprehensive overview of Ambient Backscatter Communications (AmBC) and its literature. The paper covered the basic principles of the technology, a new taxonomy based on the type of ambient signals, a review of different systems, potential applications, and open issues for future research. However, this survey did not delve into AI-based BC systems. The authors in [26] tackled the challenge of short range and low data rate in BC by introducing the concept of RIS into BC systems, making wireless propagation fully controllable and customizable while being cost-effective and efficient. The article covered three modes of RIS-assisted BC and highlighted its potential improvements in throughput and efficiency. The authors also discussed the basics of RIS technology and its integration with BC, leading to the introduction of RIS-assisted NOMA-enhanced BC. However, this paper did not focus AI based BC.

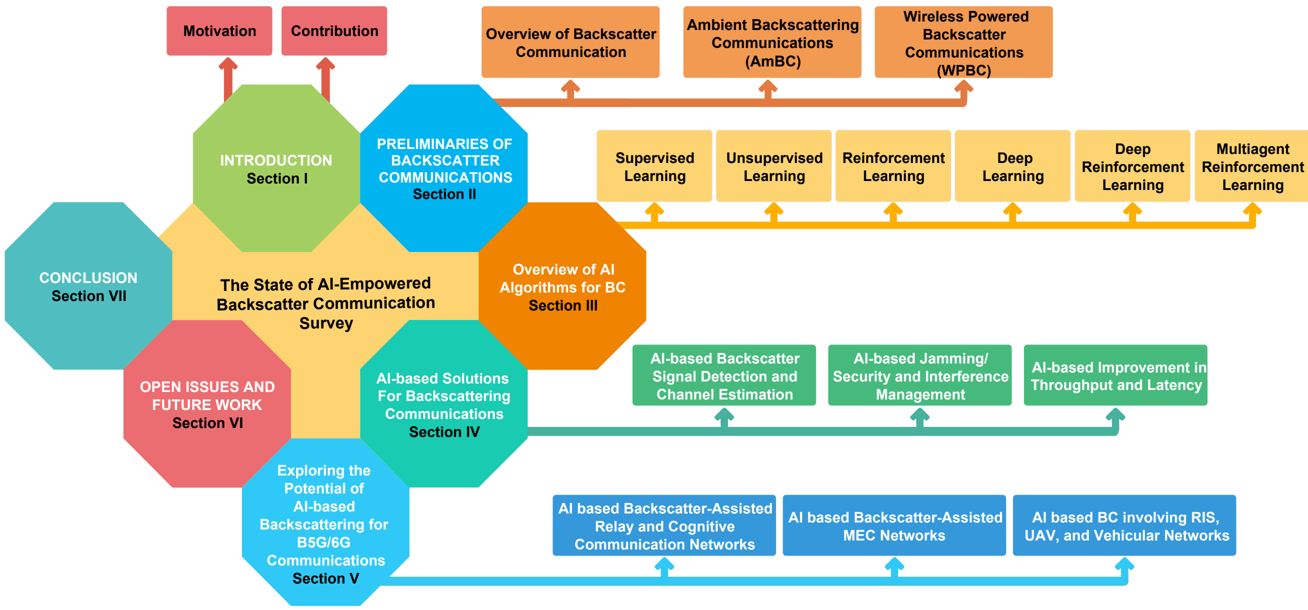

Fig. 1: Taxonomy of the survey

B. Contribution

Considering the existing surveys listed above [20]–[26] there is an open gap and an intense need for a comprehensive survey on the AI merger with BC. As shown in the taxonomy Fig. 1, our survey discusses AI-based BC solutions for technical issues and AI-based BC integration with 5G/6G technologies. The primary contributions to our article are as follows:

- Based on the existing literature on AI-based backscattering communication, we compiled a detailed review of current developments. We present an introduction to BC and an overview of the AI algorithms used in BC to provide theoretical analysis and serve as a quick reference for both novice and seasoned researchers.
- We break down the AI-based BC solutions into their parts and provide an in-depth comparison and analysis of the works in backscatter signal detection and channel estimation, interference and jammer management, and throughput and latency enhancement, respectively. Moreover, summary tables are presented for each subcategory to acquire deeper insight and capture the logical link of the different schemes from multiple aspects, such as AI domain and algorithm kinds, model elements, and optimization aims.
- For AI-based BC involving B5G/6G technologies, we also describe, compare, and analyze the research works under each sub-category, i.e., AI-based backscatter-assisted relay and cognitive communication networks, AI-based backscatter-assisted MEC networks, and AI-based BC involving RIS, UAV, and vehicular networks, respectively. Moreover, a summary table considers several aspects to aid the reader in comprehending the AI-based schemes.
- Finally, the article offers insights into the future of AI-based BC by identifying outstanding issues and suggesting open research areas. Also, it provides valuable guidance for researchers looking to explore this rapidly evolving field, highlighting key challenges and opportunities that must be addressed to realize the full potential of AI-based BC.

The rest of the survey is structured as follows: Section II presents an overview to get acquainted with BC and its variants. Section IIIcovers the AI algorithms used in BC, including supervised, unsupervised, RL, DL, DRL, and MARL. In Section IV, we provide AI-based approaches to addressing the issues of signal detection and channel estimates, avoiding interference/jamming and ensuring security, boosting throughput, and decreasing delay. Following that, Section V delves into the topic of how AI-based BC impacts B5G/6G technologies that includes relay, cognitive communication, MEC, RIS, UAV, and vehicular networks. In Section VI, open challenges and future works are presented. Lastly, Section VII concludes the survey. Table I contains a list of all related acronyms.

II. Preliminaries of Backscatter Communications

A. Overview of Backscatter Communications

In 1948, the notion of BC was introduced [23]. It is now the most promising field of research in the communications industry. BC is a technique in which the transmitter communicates signals to the receiver by re-modulating and reflecting already present signals, as opposed to producing its own signals. This approach eliminates the requirement for a local oscillator and other power-hungry, cumbersome, and costly components. The signal source, the backscatter

TABLE I: List of Important Abbreviations

Abbreviation	Definition	Abbreviation	Definition
BC	Backscattering Communication	IoT	Internet of Things
OOK	On-Off Keying	RFID	Radion frquency Identification
WiFi	Wireless Fidelity	D2D	Device to Device
LoRa	Long Range	CSI	Channel State Information
MIMO	Many Input Many Output	QoS	Quality of Service
RL	Reinforcement Learning	RNN	Recurrent Neural Network
CNN	Convolutional Neural Network	AmBC	Ambient Backscatter Communication system
ADC	Analog to Digital Converter	PB	Power Beacon
DDPG	Deep Deterministic Policy Gradient	HTT	Harvest Then Transmit
DDQN	Double Deep Q Network	SDN	Software Defined Network
DL	Deep Learning	SMDP	Semi-Markov Decision Process
DQN	Deep Q Network	SWIPT	Simultaneous Wireless Information and Power Transfer
DRL	Deep Reinforcement Learning	UAV	Unmanned Aerial Vehicles
DSRC	Dedicated Short Range Communication	WPBC	Wireless Powered Backscatter Communication
WPCN	Wireless Powered Communication Network	HAP	Hybrid Access Point
FSK	Frequency Shift Keying	V2V	Vehicle-to-Vehicle
QAM	Quadrature Amplitude Modulation	AI	Artifical Intelligence
BER	Bit Error Rate	DTL	Deep Transfer Learning
MMSE	Minimum Mean Square Error	MAC	Media Access Control
MBS	Macro-cell Base Station	SVM	Support Vector Machine
MDP	Markov Decision Process	JRC	Joint Radar Communication
ST	Secondary Transmitters	SINR	Signal to Inference and Noise Ratio
MEC	Multi-access Edge Computing	VI	Value Iteration
LPDA	Log Periodic Dual Dipole Antenna	VM	Virtual Machine
DDNN	Deep Dueling Neural Network	SDN	Software Defined Networking
BSN	Backscater Sensor Nodes	NSP	Network Service Provider
SADOL	Single Agent Aeep Option Learning	MADOL	Multi Agent Deep Option Learning
ANN	Artificial Neural Network	BS	Base Station
AC	Actor Critic	MARL	Multiagent Reinforcement Learning
LRT	Likelihood Ratio Test	DDQL	Double Deep Q-Learning
MOGA	Multi Objective Generic Algorithm	DDQL	Double Deep Q-Learning

transmitter with backscatter antennas, and the backscatter receiver are the three major components of a conventional BC system [27]. The signal source may be a permanent or specified signal generator, an ambient TV station, or a tower signal. Once the signal is detected at the backscatter transmitter, the backscatter antennas will re-modulate [28] and reflect those signals to broadcast the information. The backscatter receiver will detect the signal reflected from the backscatter antennas and decode it to extract the information transmitted by the backscatter transmitter. Controlling the impedance of the backscatter antennas while reflecting signals to the backscatter receiver [12]. The operation of backscatter antennas is easily understood by assuming two states, reflecting and non-reflecting. On-Off Keying (OOK) is a modulation system [29] in which bits "0" and "1" at the backscatter transmitter are modulated onto the reflected signals. Transmission of data bit "1" indicates the reflecting status of the backscatter antennas; similarly, the transmission of data bit "0" switches the antenna into non-reflecting mode. At the backscatter transmitter, the sequence of "0" and "1" data can be modulated into the reflection signal and then communicated to a receiver. The receiver will then precisely decode the data based on the changes in signal strength.

1) BC's Types: Especially with the IoT, [30] BC enables battery-free applications. Using the surrounding signals already accessible for data transmission, the transmitter does not need to generate its signal; instead, it must reuse the surrounding signals to send data. Based on its structure and architecture, the BC system is divided into monostatic and bistatic backscatter communication.

In the architecture of monostatic BC, the signal source and backscatter receiver are on the same device (Mono = 1, signal and receiver are located on the same device) [31]. In a monostatic BC system, the incoming signal from the signal source travels to the transmitter as an excitation signal and excites the transmitter; following excitation, the transmitter modifies the sent information and reflects it to the backscatter receiver. Radio Frequency Identification (RFID) makes considerable use of monostatic design, and the transmitter and receiver are referred to as an RFID tag and an RFID reader, respectively. There are three types of transmitters in monostatic BC: active, passive, and semi-passive, as shown in Fig. 2. The active transmitter has an internal power supply, and the transceiver may actively transmit data and has an expanded communication range. The passive transmitter is powered by energy collection and has no internal power supply. It is compact, inexpensive, and has a straightforward design. On the other hand, a semi-passive transmitter combines active and passive transmitters and only sends data when activated and supplied with an internal power supply. In order to avoid self-interference in this system, the incident and reflected signals must use separate frequencies. Even so, two-way path loss still causes incidental and reflected path losses, limiting communication range.

In a bistatic BC system, the signal source and receiver are positioned in separate places, with the signal source being

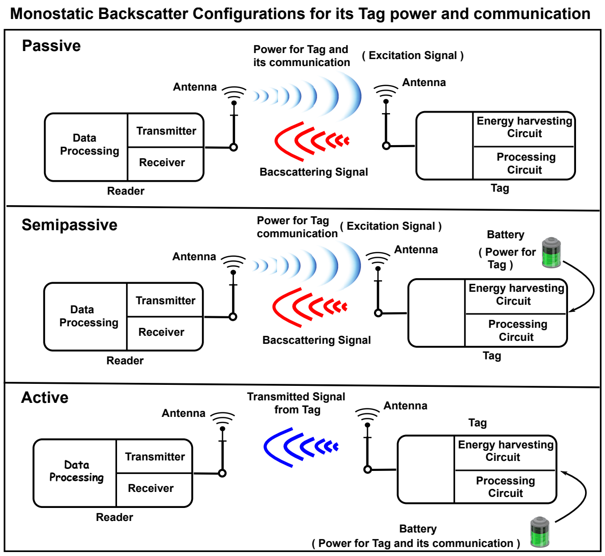

Fig. 2: Illustration of monostatic configurations that include passive, semipassive, and active.

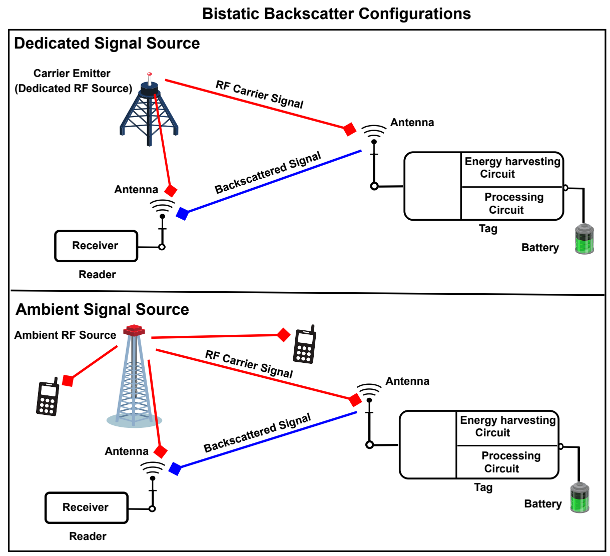

Fig. 3: Illustration of bistatic configuration with a dedicated and ambient signal source.

either a dedicated or ambient signal source, as shown in Fig. 3. Bistatic BC avoids the two-way path loss observed in monostatic BC, which is its primary benefit. To overcome the problem of two-way path loss, a signal source near the backscatter transmitter employs a unique carrier emitter. Thus, it avoids the two-way path loss and improves its overall performance. Common characteristics of BC include an antenna for backscatter at the transmitter, minimal power consumption, and a weak backscatter signal at the receiver [20].

2) BC's Issues: As with any technology, the implementation of BC systems brings a set of challenges that must be addressed to achieve optimal performance. In this part, we explore the primary issues, including signal detection and channel estimation, interference management, information confidentiality, communication range, networking, and low data rates, which are given as follows:

a) Signal Detection and Channel Estimation: In BC, signal detection is crucial for improving the communication throughput [32]. However, due to the nature of BC, which leverages the RF signals from the surrounding environment, signal detection becomes challenging as the shared spectrum makes it difficult to obtain Channel State Information (CSI). This heterogeneous nature of the signals used in BC makes it difficult to obtain accurate CSI, which is crucial for signal detection. Despite this, the availability of CSI is important for improving system efficiency, transceiver design, and security. The lack of knowledge about the RF signals and the channels' inconsistencies at reflective and absorptive states further pose challenges for channel estimation [33].
b) Interference Management : It is challenging to manage interference in a small-powered BC system [34]. The transmitting nodes cannot receive feedback from neighboring nodes; consequently, they lack information and scheduling for signal transmission [35]. In this manner, all nodes transmit data simultaneously, causing interference between the backscattered signals of different nodes, ultimately degrading the quality of the received signal [36].
c) Information Confidentiality: BC system utilizes RF signals for transmission, and these RF signals are typically vulnerable to eavesdropper attacks. Nearby eavesdropper tags could use these RF signals. Numerous security measures are implemented to combat these threats, including selecting the most effective relay scheme to evade the eavesdropper's attack [37], [38]. The eavesdropping attack poses a significant risk to the information carried by backscattering signals.
d) Communication Range: Although the nature of the backscatter systems limits the communication range of the backscatter reader and tag, many efforts have been made to overcome this limitation. These efforts include the use of various coherent receivers, Long Range (LoRa) [39], Backscatter quantum tunneling [40], power amplifier [41], and multi-antenna systems [42]. In addition, backscattering aims to provide a battery-free environment while maintaining a similar communication range. As a result, increasing the method's effectiveness is crucial.
e) Networking: Networking is another significant issue for the BC system. Backscattering is based on a battery-free and low-energy environment, which the network must support. [43] analyzed this issue and envisioned the backscatter node as a virtual transmitter that handles several tags (100 to 1000). More improvement is needed to enhance the networking area of backscattering communications.
f) Low Data Rate: The backscattering technique uses the

available RF signals to modulate their information; nevertheless, the data rates of backscattered signals are relatively low. However, there needs to be more data rate to run in an IoT context, and it also limits the potential of 5G applications. Therefore, meeting the needs of future BC in IoT devices can be accomplished by obtaining high data rates [25].

3) BC's Techniques: Future IoT-based applications will rely on BC systems to enable long-distance, low-latency, and high-rate device connectivity. Following is a brief overview of several sophisticated backscattering techniques:

a) BC with Power Beacon (PB): Backscattering tags that are used in the IOT has dual tasks, sensing and computing; as a consequence, they require more energy. For this, we use a technique BC with a power beacon that could enhance the energy throughput. The beamforming [44] and multi-antenna Power Beacon for this PB must-have CSI for getting higher energy. Similarly, Another strategy for increasing power efficiency is optimizing the Continuous Wave (CW). This design aims to increase the PB signal's peak-to-peak power ratio, yielding higher energy-harvesting efficiency due to its linearity.
b) Full Duplex BC: In future IoT, there would be a large number of tag-to-reader connections operating at the same time. Although the information flow in RFID is unidirectional, it may still result in jitter, interference, and other channel errors [25]. Utilizing full-duplex communication can efficiently minimize the latency and improve the capability of spectrum utilization of IoT readers.
c) Time Hopping BC: Interference with high node density in IoT networks is a design challenge in BC [25]. IoT devices that can behave as sensors in smart homes and cities can be utilized to tackle interference. A transmission technique known as the time-hopping spread spectrum can be used to overcome this challenge. At the same time, each tag can randomly choose a single slot in N, and the time slots for sending a symbol and choosing different tags are independent and unique.
d) MIMO BC: The most common loss in the BC is double path loss since the backscattered signal at the tag propagates in a closed-loop channel cascading in the uplink and downlink channels. One solution is to use the rays of an antenna (MIMO) [45] at tag and reader, deploying spatial-diversity techniques to enhance the channel reliability and reduce these losses.

B. Ambient Backscattering Communications (AmBC)

Have we ever thought of a world where small, compact devices can communicate without relying on any external power source? The concept of Ambient Backscattering Communications (AmBC) makes this dream a reality [46]. By harnessing the energy from ambient RF signals, AmBC enables seamless communication between devices without needing a dedicated power source, making it a low-cost and low-power solution for IoT networks. AmBC has the potential to revolutionize the way we think about device communication. Using existing ambient signals from TV towers, FM/AM base stations, or cellular BSs, the AmBC system reduces the cost and power consumption of the communication, eliminating the need for additional energy sources [47]. The three essential components of AmBC are: (1) the ambient RF signals, (2) the backscatter transmitter, and (3) the backscatter receiver. These components work together to enable energy-efficient and cost-effective communication. The energy harvester within the backscatter transceiver collects energy from the ambient RF signals, which the transmitter modulates and reflects on transmitting data. The receiver detects these modulated RF signals, decodes the data, and completes communication. Finally, the backscatter transceiver, which integrates the energy harvester, transmitter, and receiver, connects to a common BS or antenna, creating a self-sustaining communication system.

However, the design of AmBC systems has its challenges. The weak, random, and uncontrollable nature of ambient backscatter signals poses limitations for the extraction and decoding of data. Conventional power-hungry receivers and complex decoding schemes are unsuitable for battery-free environments, restricting the design space. AmBC does not have a centralized controller, so it relies on multiple access protocols for communication management and carrier sensing capabilities. Interference from other ambient RF sources may limit the bitrate and transmission range, and noise and fading can further degrade the communication channel [25]. Despite these constraints, AmBC is considered legal and does not require a dedicated frequency spectrum, making it a promising technology for the future of IoT networks.

C. Wireless Powered BC (WPBC)

The world of connected devices is constantly evolving and growing, with intelligent devices permeating every aspect of our lives. From the tiny sensors in our bodies to the walls of our homes and beyond, the IoT creates an intelligent environment that relies on billions of connected devices communicating. However, powering these tiny IoT devices can be a challenge. With their nano-architecture and design, powering them with batteries is costly and requires constant maintenance [48]. To address this challenge, researchers have devised a new approach called WPBC.

In this architecture, Power Beacons (PB) are deployed to wirelessly powered backscatter D2D links, allowing nodes to modulate and reflect signals sent from PBs to transmit their data. This design offers more power delivery than energy harvesting and is suitable for large-scale, dense IoT networks with relatively high data rates [9]. However, this solution has its challenges. For example, a co-existing transmitter can result in mutual interference and lower data rates, and BC networks lack scalability due to their dependence on ambient RF signals.

Historically, Energy Harvesting (EH) technology has developed in three primary directions: Simultaneously Wireless Information and Power Transfer (SWIPT) [49], Wireless Powered Communication Network (WPCN) [50], and Wireless Power Transfer (WPT) [51], [52]. In WPCN, devices harvest energy from a hybrid-access point and then use this stored energy to transmit data. In SWIPT, a single signal carries energy and information, enabling energy-constrained devices to receive both simultaneously. Moreover, in WPT, a dedicated power transmitter transfers energy only [51]. As the world of connected devices continues to expand, it is exciting to imagine the possibilities and advancements that the future of IoT will bring. With new approaches like wireless-powered BC and the continued development of EH technology, we are on the cusp of a truly intelligent and connected world.

III. Overview of AI Algorithms for BC

AI, a field that aims to create robots with human-like behavior and intelligence, is the technology frontier, as outlined in [53]. Remarkable strides have been made in this endeavor, with AI programs like Alpha-Go demonstrating the vast potential of machines with tens of millions of parameters. Our path toward true AI requires a diverse range of approaches and techniques. The integration of AI in various domains is a testament to its recent technological advancements.

Machine Learning (ML), as specified in [54], is a critical component of AI. It involves two crucial steps: training and prediction. A good ML model starts with a solid foundation, a vast and diverse dataset that sets the accuracy bar for its predictions [55]. The model is then trained on this data, and its settings are optimized. The larger the data's diversity, the more influential the training process. Nevertheless, the quest for ML excellence is never-ending, and the model must be continuously refined. Before we delve into the complexities of Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL), let us first introduce the supervised (i.e., Section III-A) and unsupervised learning (i.e., SectionIII-B) techniques. Then, we will delve into RL (i.e., Section III-C), including traditional RL algorithms, followed by a comprehensive examination of Deep Learning (DL) and its cutting-edge DRL algorithms as shown in Fig. 4.

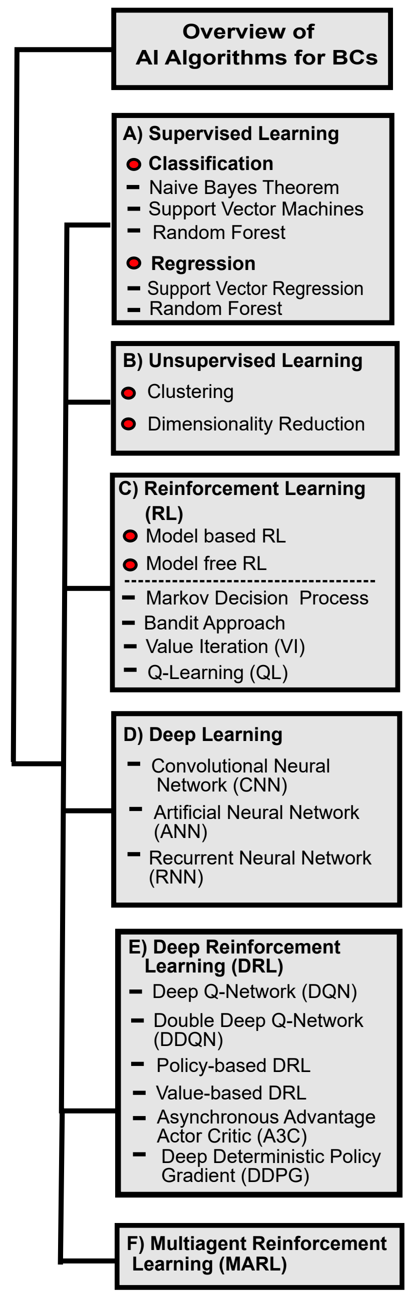

Fig. 4: Overview of AI algorithms for BC

A. Supervised Learning for BC

Supervised Learning (SL) attempts to learn data mapping from input to output using the labeled data sets as a guide. In SL, for example, the input and output data tend to be consistent with one another [56]. Finding such input/output mapping relationships is a primary goal of SL. There are two main types of SL algorithms, regression and classification.

1) Classification: The main difference between classification and regression is that regression algorithms are used for continuous data, while classification is for discrete data. The output results of classification algorithms are restricted to discrete data, such as picture classification prediction, spam identification, verification code recognition, etc. Consider the case of handwritten digit recognition, where the dataset consists of just the ten Labels 0–9. Once the model is trained, the goal is to identify the range of numbers to which the input data belongs, between zero and nine. Decision tree and SVM are two common examples of classification algorithms [57].

Naive Bayes Theorem : It is a probabilistic classifier based on Bayes's theorem. It calculates the probability of an event based on prior probabilities of related events. The theorem can be applied to continuous and discrete data, and it is widely used in classification problems due to its simplicity and speed [58]. In addition, Naive Bayes classifiers can be easily scaled to large datasets with little additional training data and can provide near-real-time forecasts. However, a potential flaw of the theorem is zero frequency allocation, which assigns a zero probability to a variable whose value is missing from the training dataset [59].

Support Vector Machine (SVM): It is a powerful ML tool that handles various data types, including unstructured and semi-structured data. SVM's ability to handle non-linear data using the Kernel Trick makes it well-suited for BC systems, where the signal modulation can be non-linear [60]. For example, SVM could classify data in a BC system, where information is transmitted by reflecting a signal to the sender. In this system, the receiver uses backscattering to modify the signal's amplitude or phase to convey information to the transmitter. SVM could be used to classify the modified signal and decode the information transmitted by the BC system. However, SVM has limitations when processing large datasets, and selecting the right kernel function and hyperparameters can be challenging [61]. Nonetheless, SVM remains a versatile and powerful tool in ML, capable of solving complex problems and achieving high accuracy.

Random Forest: It is an ML algorithm that can be used for classification and regression problems. The algorithm is based on ensemble learning, which involves creating multiple models and combining their outputs to produce a final prediction [62]. In the case of a Random Forest, the algorithm generates a group of decision trees from the input data. The trees are created by randomly selecting subsets of the data and using them to train individual decision trees. The aggregate output of all the decision trees is then calculated to produce the final prediction [63]. One of the main advantages of using the Random Forest method is its easy handling of large amounts of data. Additionally, the algorithm produces intuitive output, making it easier to interpret and use for decision-making. However, as more trees are added to the forest, the complexity of the model increases and more storage space is required to store the model.

2) Regression: Regression algorithms are indeed well-suited to solving continuous-variable problems, such as predicting housing prices, airport traffic patterns, and box office success for movies. These algorithms aim to find a function that maps the input variables to the output variable [64].

B. Unsupervised Learning for BC

Unsupervised learning is an ML approach that uses unlabeled datasets to discover patterns and relationships in the data. Clustering algorithms are a common technique used in unsupervised learning to group data into categories based on their similarities [65]. This approach is useful when obtaining labeled data is expensive or not feasible. In addition, unsupervised learning finds applications in various fields, such as data mining and image processing, to uncover hidden relationships and insights in large and complex [66].

C. Reinforcement Learning for BC

RL is an ML approach where an agent learns to make decisions to maximize a cumulative reward. RL has been applied in BC to optimize communication parameters based on performance feedback. Agents learn to maximize the cumulative reward in RL by interacting with the environment [67]. The agent learns to make decisions by taking in information about the environment as it is (i.e., its current state) and then determining what kinds of actions it could take by interacting with that environment to maximize the system's reward. Upon completing the action selection, the agent receives a reward and a limited set of possible future states of the environment. The agent's performance in the current state is evaluated quantitatively based on the success or failure of the actions it has chosen (known as a reward) [68].

The similarities between the RL model and the way people learn are striking. Consequently, it is near to attaining perfection. During the training phase, the model is capable of correcting any faults that occur. Once the model has addressed an error, the likelihood of the identical error occurring again is extremely low [69]. Moreover, It can generate the optimal solution model for a particular problem. Also, learning from experience is possible even without access to a training dataset. An excess of reinforcement learning can result in an overabundance of states, which can degrade the results. Similarly, for trivial problems, RL is not the method of choice [70]. There is a significant computational and data requirement for RL. The system has an insatiable appetite for information.

RL is further categorized into the following two main research fields:

1) Model based RL: In this form of RL, environmental factors are determined beforehand to simulate the environment's response to the agent, making it suitable for adjusting communication parameters. For example, they are transitioning from state s to the next state s' by performing action a at the current time t. It consists of six components (agent, action, reward, environment, state, and objective) to simulate the environment's response to the agent [71]. As a result, the agent predicts the action for a state s at time t. In addition, the agent requires the starting state to forecast the action, and the next state is computed based on a probability that considers the current action selection and the current state.

2) Model free RL: One of the primary distinctions between model-free RL and model-based RL is that model-free RL cannot anticipate the next state based on the current state, instead relying on "trial and error" approaches [72]. In this technique, the agent explores the policy space by evaluating the numerous incentives and selecting the optimal action, considering the reward. Following is a list of the most common approaches employed in RL.

Markov Decision Process (MDP): It is a mathematical framework commonly used in RL to model decision-making situations [73]. An MDP consists of a set of states, actions, and rewards that define a decision-making problem. In an MDP, an agent interacts with an environment by taking actions in states and receiving rewards. Furthermore, the agent aims to find a policy that maximizes the expected cumulative reward over time. The state transitions and rewards are determined by a Markov property, which states that the future depends only on the present state and not history. MDP is a powerful tool for modeling decision-making problems in RL [74]. MDP provides the best and most accurate decision-making solution, especially where the outcomes are random or partly influenced by the decision-maker. However, it becomes inefficient when states become larger and more complex. Moreover, it requires a system model for higher states, which is quite challenging to build.

Bandit Approach: The Bandit algorithm, named after a slot machine with multiple arms, is a popular approach in ML for allocating limited resources to competing options to maximize the expected profit [75]. In the field of BC, Bandit algorithms are used to optimize the communication parameters for maximizing the system's overall performance. This is particularly useful when BC systems are highly mobile and dynamic, such as healthcare, finance, and online commerce. However, the basic Bandit algorithms do not consider the system's current state, potentially ignoring valuable information that could assist in choosing the best action [76].

Value Iteration (VI): Dynamic programming (DP) is the basis for the value iteration approach. A greedy strategy, in which the agent picks the action with the highest value, is the most natural and straightforward way to determine the optimal policy. The problem may have overlapping subproblems and an ideal structure. Because of this, a DP-based algorithm will serve its needs well [77]. The primary goal of opting for the greedy approach is to pick the best possible state by using or computing the system's value. This is done by continuously updating the policy state until the optimal policy is reached. Value iteration has several benefits and is straightforward to implement, but it is based on DP and requires constant iteration. As a result, it is less efficient in complex state settings [78].

Q-Learning (QL): BC can benefit from using RL algorithms, such as Q-learning. In this model-free approach, the agent learns the value of a specific state's action through trial and error, using a greedy strategy to select the next action based on the highest value [79]. In the context of backscattering, the agent can use QL to optimize communication by selecting the optimal transmission protocol and adapting its parameters to the environmental conditions. For instance, QL has been used to improve the energy efficiency of BC systems by selecting the most suitable modulation and coding schemes. By learning from the environment and adapting to its changes, QL can enable BC to achieve better performance and reliability. However, QL also has some limitations, such as its reliance on online updates, which can be time-consuming and resource-intensive in some cases.

Next, we review the DL-based and associated methods proposed in the field.

D. Deep Learning for BC

Most traditional ML algorithms must be trained before deployment due to increased power and time requirements. Therefore, training the model before it is used in production can be expensive. In order to address the issue and lessen the training burden, DL is the most effective method currently available. It consists of several different layers of neurons [80]. DL has shown promising results in improving the performance of BC systems. By leveraging the power of DNNs to learn complex relationships in data, DL can help overcome the limitations of traditional signal processing techniques and enable more efficient and reliable BC. There are a few well-known DL algorithms, including Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and Recurrent Neural Networks (RNN). Deep neural networks mimic human observation and monitoring by inspecting data like a human would when looking at a problem. Simply put, its working process consists of many layers performing repetitive steps, where the first steps obtain generic data as input for data model learning and keep adding new data as the number of steps increases [81].

Based on the following factors, the DL is deemed to be superior to other ML techniques:

1) In model training and prediction, DL-based algorithms are regarded as more effective due to the capacity of DL to manage enormous amounts of data and its scalability.
2) Automatic and hierarchical data extraction is made possible with the help of DL. The high-level correlations and core characteristics can be extracted from the input data.
3) DL reduces the computational and temporal complexity as a single trained model is well suited for multiple tasks.

The main drawbacks of DL include the requirement of a massive dataset, optimization techniques, and storage requirements.

Now, we review the methods utilizing RL and DL methods, i.e., the combination of RL and neural network-based methods.

E. Deep Reinforcement Learning for BC

The key idea is that the DRL agent learns to make optimal decisions based on the current system state in order to maximize the overall performance of the BC systems. In order to obtain reward feedback in a loop, the DRL method takes inspiration from neural networks, precisely function approximators [82]. From then, the decision-maker can iteratively filter his next move; this technique has applications in BC systems for resource allocation, channel estimation, scheduling, beamforming, cooperative communication, etc. [83]–[85]. Additional subtypes of DRL include:

Deep Q-Network (DQN): The Deep Q-Network (DQN) algorithm optimizes the action-value function using a DNN [86], [87]. It was applied to Atari games, where it takes multiple game frames as input and returns state values for each action. The stability issue in DQN was resolved through experience replay, which involves saving small sessions of records, actions, and states in the system's replay memory to train the Q-network. The DQN algorithm is notable for preventing instabilities and convergence and preventing the state-action space from expanding too rapidly. However, its learning rate for the agent may be slower, and its sample complexity may increase.

Double Deep Q-Network (DDQN): Double Deep Q-Network (DDQN) is a variant of the DQN algorithm, a DRL algorithm that combines a deep neural network with Q-learning. DDQN was proposed by Hasselt [88] to address the overestimation bias in the original DQN algorithm. It uses two separate NNs, an online network, and a target network. The target network generates target values for training the online network, and the online network generates action values during the agent's interactions with the environment. As a result, the target network is updated less frequently, stabilizing the training process and reducing overestimation bias. DDQN has been effective in solving various challenging reinforcement learning problems. However, it increases the system's complexity and may result in latency issues due to having two functions, one for estimating the advantage function and another for the value function.

Policy-based DRL: In a policy-based method, a mapping from states to actions is directly learned and improved through interactions with the environment [84]. Unlike value-based DRL, where the agent must first learn the value function before improving the policy, policy-based methods directly optimize the policy by updating the parameters of a parametric policy function. Policy-based methods can be more sample efficient, as they can directly learn from the reward signal, but they can also be less stable and harder to converge than value-based methods. Policy-based DRL can be used in problems with high-dimensional or continuous action spaces, where the optimal policy may be difficult to represent as a value function.

Value-based DRL: The value function in RL predicts the expected cumulative reward an agent can receive following a particular policy, starting from a given state or state-action. It estimates how good it is for the agent to be in a particular state or to take a specific action. The value function can improve the policy by finding the action that leads to the maximum value in each state [89]. There are two main types of value functions: state-value function and action-value function. In value-based DRL, the agent's efficiency is measured against the value function, which improves the policy by finding the action that leads to the maximum value. The value-based approach is used in large state spaces where it is infeasible to visit all possible states and actions.

Asynchronous Advantage Actor-Critic (A3C): Actor-Critic (AC) algorithms are a type of RL algorithm that combines both value approximation and policy gradient. The algorithm consists of two main components, the "actor" and the "critic." The actor is a neural network that outputs actions, while the critic is another neural network that evaluates the action values of the actor-network. The AC architecture has been further improved with the A3C algorithm, which is highly efficient and requires minimal resources and samples for learning [90]. AC-based algorithms use stochastic techniques to select actions and solve RL problems. However, the rapid acquisition of information can slow down the calculation process.

Deep Deterministic Policy Gradient (DDPG): The DDPG (Deep Deterministic Policy Gradient) algorithm is a DRL algorithm that combines the advantages of both deterministic policy gradients and actor-critic methods. It uses low-dimensional observations to learn an optimal policy. It uses four DNNs (actor-network, actor-target-network, critic-network, and critic-target-network) to approximate the actor and critic functions. The algorithm also has replay and target networks, which help maintain stability during the learning process [91].

The MADDPG (Multi-agent Deep Deterministic Policy Gradient) can train multiple agents to coordinate and collect data in uncertain environments in a multi-agent scenario. However, finding the right hyperparameters for DDPG can be task-dependent and unstable, but slow-moving target values help to maintain stability during learning. Single-agent RL algorithms train a single agent to find the optimal policy for a task. In contrast, multi-agent RL algorithms use multiple agents to find the optimal policy through competition or coordination.

F. Multiagent Reinforcement Learning (MARL)

MARL is a new subfield of RL that focuses on developing algorithms that allow multiple agents to learn from their interactions with each other and their environment [92]. MARL aims to build systems that can solve complex problems through cooperation and coordination among multiple agents. This can lead to more efficient and effective solutions than those produced by individual agents working alone [93]. Experience sharing between many makes agents get better throughput and learn faster. However, it has many more advantages. The big challenge in MARL is the curse dimension due to multiple agents, which means when many agents cooperate, action space increases, and thus it becomes more challenging to handle than a single agent [94].

IV. AI-based Solutions For BC

The wireless world has been revolutionized by the introduction of backscattering technology, paving the way for a battery-free communication ecosystem [25]. This innovation in wireless communication presents a novel and compelling solution, yet it faces several challenges that need to be overcome [95]. However, the integration of AI in backscattering has come to the rescue by offering cutting-edge algorithms and techniques to tackle these challenges. AI optimizes the transmission of signals, mitigating interference and enhancing security parameters. AI can also monitor and analyzes the backscattered signals to address the limitations

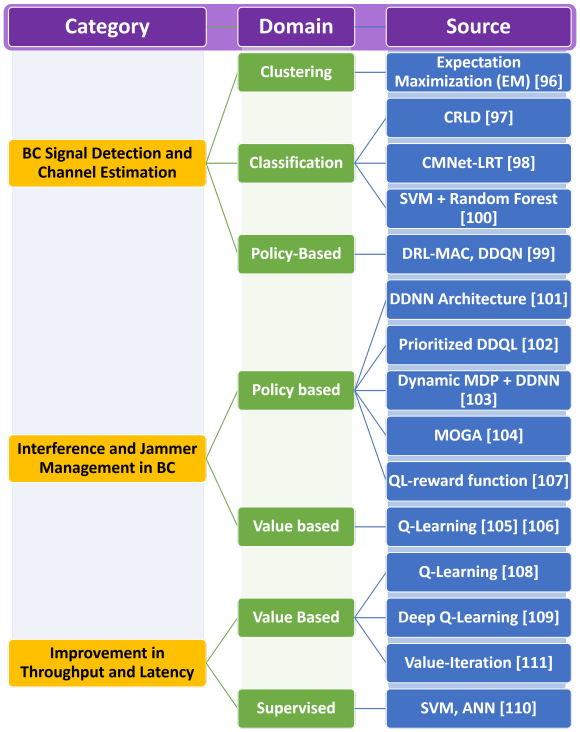

Fig. 5: Different categories of AI based Solutions for Backscatter Communications under different AI domains leveraging different algorithms

of backscattering in terms of throughput and latency. This section will explore AI-based solutions to the issues of signal detection and estimation, security and jamming, and throughput and latency in BC systems utilizing different algorithms, as shown in Fig. 5. For a comparative analysis of AI-based backscattering solutions, a summary Table II is also presented, providing a clear and concise understanding of the different schemes and their outcomes for BC systems.

A. *AI-based Backscatter Signal Detection and Channel Estimation*

This subsection explores AI-based techniques for signal detection and channel estimation in BC systems as shown in Fig. 6. These techniques utilize ML algorithms to enhance accuracy and efficiency in detecting signals and reduce bit error rates. They also include a medium-access control protocol based on DRL to optimize backscatter communications and mitigate interference with WiFi. These innovative methods have the potential to revolutionize communication in BC systems and lead to improved performance and reduced power consumption. The authors of this paper [96] proposed a new signal detection method for AmBC systems using ML. The primary motivation behind this research is the growing interest in AmBC systems due to their low power consumption, which makes them ideal for connecting billions of IoT devices in the future. However, detecting signals in AmBC systems can be challenging due to the difficulties in predicting communication channels and sharing the spectrum. The proposed method starts by exploring and clustering the characteristics and qualities of the received signal using unsupervised learning. The authors then use cluster-bit mapping to detect the signal, even when noise power and channel estimation are unknown. Two detection approaches are presented, one with $N > 1$ spreading gain and the other with $N = 1$ spreading gain. The latter approach, optimal for the desired outcomes, maximizes detection efficiency by computing the detection thresholds. The results of the simulations show that the proposed method outperforms baseline approaches and can help to improve communication performance and reduce power consumption in AmBC systems.

In another work [97], Liu et al. aimed at improving signal detection in BC systems by reducing the Bit Error Rate (BER). In BC systems, estimating CSI is often challenging, resulting in a high BER in the baseline tag for signal detection algorithms. The authors proposed solving this issue by developing a Deep Transfer Learning (DTL) based method. The method involved using a novel Covariance Matrix-aware neural Network (CMNet), which employed offline learning, transfer learning, and online detection to capture the dynamic nature of the wireless environment and improve signal detection accuracy. The CMNet was evaluated using a likelihood ratio test based on the Minimum Error Probability (MEP) criterion. The authors first trained the CMNet using offline learning to capture the statistical properties of the channel models. Transfer learning was then used to fine-tune the network to the current channel. The well-trained CMNet was then employed for online signal detection. The simulation results showed that the proposed CMNet performed better than other methods in accuracy and efficiency, even without CSI. However, while the CMNet shows promising results, its high computational needs may limit its feasibility for some applications. Additionally, its applicability to all BC systems remains to be determined through further research. Similarly, in [98], the authors focused on finding the optimal solution to the channel estimation problem in AmBC. Channel estimation is regarded as a de-noising problem, and a CNN-based deep Residual Learning De-noiser (CRLD) was created to restore the channel coefficients. A three-dimensional (3D) de-noising block is designed to simultaneously examine pilot signals' spatial and temporal characteristics to support de-noising in CRLD. This innovative CRLD-based estimation scheme consists of the online estimation and offline training phases. The proposed CRLD employs multiple 3D de-noising blocks to intelligently explore spatial and temporal signal characteristics, enhancing estimation precision. According to simulation results, the proposed system achieves near-optimal performance using the MMSE method.

The authors of this study proposed a novel Medium-Access Control (MAC) protocol based on DRL (DRL-MAC) to support and enhance IoT actions in BC [99]. This work is primarily performed to solve the problem of WiFi signal interference by utilizing the most recent WiFi infrastructure to fix the BCs that cause interference with WiFi communica-

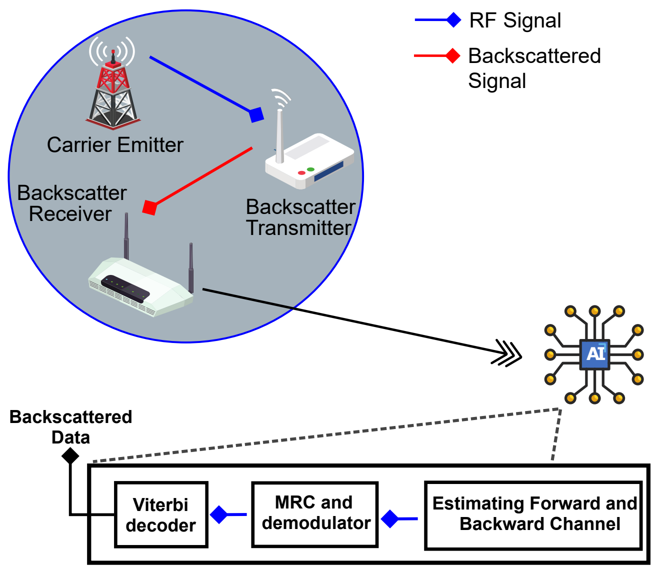

Fig. 6: Illustration of AI-based Solutions for Backscatter Signal Detection and Channel Estimation

tions. In this proposed model, DRL is also used to determine which backscatter device will be serviced and the reservation step for the serviced tag based on the reserved information. In addition, a predefined utility function is present, and the backscatter and WiFi communication optimization problems are resolved. In addition, DRL is utilized to identify the most optimal policy. A DRL-MAC integrates DRL with on-demand reserved backscatter communications using the DRL WiFi AP, which can train the tags based on the WiFi infrastructure. With the implementation of the determined action, the AP will attain a nominal throughput. Simulation results demonstrate the effectiveness of DRL-MAC.

The AmBC allows the RF-powered devices to communicate with the readers by harvesting and modulating their ambient RF signals. Unlike traditional RF identification, AmBC does not require the reader to transmit excitation signals to the tag or additional carrier emitters (RFID). This allows the AmBC to achieve low costs and an energy-efficient environment. Conventional AmBC employs an energy or Minimum Mean Square Error (MMSE) detector to detect signals with a BER. This work [100] describes an ML-based algorithm for detecting tag signals in an AmBC signal by transforming the detection problem into a classification problem. In addition, the proposed system divides the received signals into two groups based on their properties and energy characteristics. This study used two supervised ML techniques, SVM and random forest, to decode the tag symbols. In addition, additional ML features have been implemented to reduce the BER of the system. Simulation results demonstrated that ML-based detectors could achieve low BER and high throughput compared to MMSE detectors.

B. AI-based Jamming/Security and Interference Management

This subsection explores AI-based schemes for managing jamming/security and interference in BC systems as shown in Fig. 7. Traditional anti-jamming and security strategies are ineffective against intelligent jammers, so novel DRL algorithms and DNN are proposed for optimal anti-jamming strategies utilizing techniques such as deception, directional antennas, etc. These techniques aim to defend against jamming attacks and increase system throughput. AI-based schemes for managing interference involve learning to adjust transmission duration and frequency, utilizing backscattering, or harvesting energy from jamming signals. The optimal policy is obtained through RL-based QL algorithms, improving system performance.

Traditional anti-jamming strategies lack real-time protection against jamming attacks, particularly intelligent jammers based on AI. The authors of this work [101] proposed an anti-jamming architecture that combines the most advanced neural network and AmBC techniques. This framework will enable transmitters to confront and defeat jammers rather than hide or flee. In this process, the transceivers learn the jamming policy of the jammers before transmitting their data on jamming signals or backscattering and harvesting the necessary energy from the signals. Existing work utilized QL algorithms to overcome unknown jamming attacks, but these algorithms had drawbacks, such as slow convergence for optimal policy. Considering these restrictions, the authors proposed a novel DRL algorithm based on a recent dueling neural network architecture. This will cause the transmitter to learn the strategy of the jammer and adapt the necessary countermeasures. Specifically, the authors have proposed an anti-jamming algorithm for transmitters that adjusts transmission duration and frequency, backscatters data via jamming signals, or harvests energy from them. Furthermore, the authors proposed an MDP-based optimal anti-jamming strategy to obtain the optimal defense policy to learn about the jamming attack and the working nature of jammers. Similarly, deep QL and deep dueling techniques were used to achieve long-term results, maximize the average throughput, and minimize packet loss. The detailed simulation results demonstrated that the technique is more effective. The authors in [102] have devised a framework to manage the tradeoff between radar sensing and data transmission in Joint Radar Communication (JRC) systems. This paper examines an environment with intelligent and reactive jamming attacks. Initially, the authors created innovative JRC systems and deception technology to manage jamming attacks against JRC systems. Two of the technologies mentioned above have predefined functions: deception technology is used to predict and idealize the jammer's action and respond immediately or appropriately, while backscattering is used to transmit the data on jamming signals. Due to the unpredictability of jamming signals, the DRL algorithm was developed to determine the optimal policy for JRC systems. The investigation reveals that the

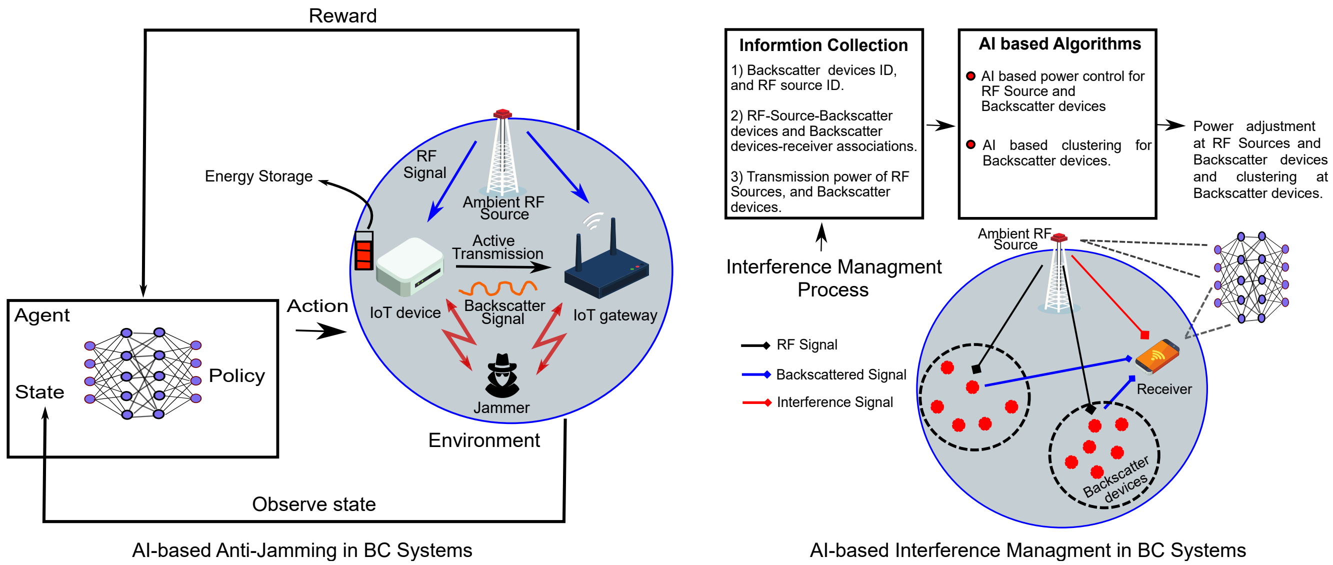

Fig. 7: Illustration of AI-based jamming/security and interference management in BC networks.

proposed system protects systems from jamming attacks and utilizes jamming signals for data transmission while increasing the system's throughput. Various RL algorithms and an MDP are used to solve the problem. Using the deception strategy and DRL algorithm, we rendered the jammer ineffective and unable to launch continuous attacks. The proposed algorithm was compared to conventional jamming techniques, and extensive simulation results demonstrated that the double-deep QL-based algorithms are more efficient and achieve higher throughput.

In another work, the authors in [103] introduced deep fake, a novel DRL-based deception technique to avoid jamming attacks. For jammers to attack a system or a channel, the jammer must detect and attack the channel if it detects only the legitimate transmitter's communications. To avoid and protect the system and channel from jammer attacks, the authors proposed a deception algorithm in which legitimate transmitters emit bogus signals, luring jammers to attack the channel. By utilizing AmBC or harvesting energy from jamming signals, the transmitter can now generate strong jamming signals for data transmission when the jammer attacks the channel. The proposed strategy has dual benefits: it defends against jammer attacks and utilizes the jamming signals to increase the system's overall throughput. However, jammer attacks are dynamic and unpredictable. Therefore, the authors proposed the DRL-based algorithm utilizing the deep-dueling network design to achieve the optimal policy many times more frequently than the other baseline RL algorithms to achieve superior results. The authors of this study avoid jamming attacks by employing deceptive techniques, transmitting fictitious signals, and decreasing the jammer's output. In addition, cutting-edge techniques such as ambient backscattering and deep dueling-based technology were utilized.

Data security is a pressing concern and significant challenge in AmBC systems because of the tag hardware. The majority of information leakage occurs in unidirectional communication channels. In this research, the authors [104] suggested the design of an antenna based on ML technique to address the challenge of information security. In which the patch antenna integrated on the Log periodic antenna is designed in such a way that they attempt to achieve directional communication from the relay tag to receiving reader. This antenna is designed to have small side lobes with high gain. The authors have used the multi-objective genetic algorithm to achieve the desired results that suppress the side lobe and enhance the antenna's main lobe, improving the antenna's overall gain, standing wave ratio, and return loss. This way, a directional antenna has been designed for the tag to achieve beamforming—the ultimate purpose of the secrecy capacity to evaluate the system's security. The secrecy capacity is the transmission rate that can be communicated reliably through the primary channel.

In this study [105], the authors sought to increase the performance of BC by employing RL approaches. For comprehension, a multi-cluster BC model for short-range information sharing is considered. Using the QL approach, the purpose is to minimize interference in the BC network. The authors attempted to satisfy the effective SINR requirements, which are met by monitoring fault logs using an agent. A feedback link is established between the RF source and the backscatter tag in order for the system to make intelligent and valuable power allocation decisions. This link will convey the learning-related feedback information. The model is constructed so that a feedback link between the RF source and tag will assist the system in intelligently allocating power, and smart decisions are made based on feedback data. This intelligent power allocation reduces interference, hence improving the SINR of the network. The agent is rewarded for appropriate behavior and punished for inappropriate behavior. The agent attempts to maximize the effect of its activity. Consequently, the feedback link and rewarding scheme enhance the power allocation criterion compared to the baseline scheme, in which the same amount of power is allocated to all network devices. The results demonstrated that this algorithm is superior to equal power distribution systems regarding SINR, capacity, and energy consumption. Future research must involve the use of numerous antennas for transmitters and receivers.

The AmBC enables the IoT and other sensor-based fields to operate without batteries. However, when we interact with the IoT, we frequently encounter interference and other jamming issues. In this manuscript [106], the authors considered the interaction between the user and an intelligent interferer in AmBC as a game. This algorithm engages the user and interferer in a well-designed utility function and considers the backscattering time. The issue arises, however, when neither the SNR of the system nor the transmission technique of the interferer is known. The authors utilized the QL algorithm to overcome this issue and arrive at the optimal strategy iteratively and dynamically. The time slot is assumed to be divided into equal intervals of one, two, three, and so on. Each time slot is assumed to be fixed, and transmission occurs within these time slots. This paper aimed to avoid interference for AmBC in which the user determines the backscattering time, and an intelligent interferer attempts to interfere with the transmission with its jamming power. User-interferer interaction is a dynamic game due to the lack of system state and interferer transmission power information. Then, utilizing QL and analytical outcomes, optimal strategies were developed. The comprehensive simulation demonstrated that the proposed work enhances user utility.

In BC, the significant interference caused by the repeated reuse of spectral resources is a major impediment. The authors in [107] proposed RL-based solutions for high-level interference management whenever backscatter tags interact with other legacy devices in heterogeneous networks. Agents are trained to reduce interference between legacy users (macro-cell) and backscatter tags (micro-cell). The appropriate rewarding function governs users' transmission power level for both macro and small cells. All BSs and the centralized controller are linked via an optical fiber link. The SDN controller regulates the power levels of macro cells and micro BSs, which are assumed to operate on channels with the same number of resource blocks. The BC devices harvest energy from nearby signals and convert it to DC. The transmission signal is typically known as the small cell BS. Consequently, it can use interference management techniques to acquire the signal from the monostatic backscatter tag. This work's primary objective is to provide a QL-based framework for addressing the interference problem in SDN. To improve the overall efficiency of multi-antenna backscatter tags, further research is required.

C. AI-based Improvement in Throughput and Latency

This subsection discusses the use of AI in improving the throughput and latency of wireless communication systems that rely on ambient backscatter signals. It highlights various approaches, including value iteration, QL algorithms, and deep QL using DNN. It also discusses using ML techniques such as SVM, ANN, and the Naive Bayes algorithm to read sensor tags and supply power in RFID-based backscattering systems. The following section provides an overview of the impact of AI-based BC on wireless communication and IoT.

By absorbing and reusing the energy from ambient backscatter signals, wireless devices can function in low- or no-power environments. In this operation, wireless devices must toggle between energy harvesting and communication. The goal of [108] is to maximize throughput under a fading channel environment by selecting an optimal operating mode. The authors presented this issue as an infinite-horizon MDP problem. They used a dual scenario when they knew the RF signal strength, and then they applied the value iteration algorithm to find the optimal decision policy. Likewise, when the signal strength is unknown, they have suggested the QL algorithm to enhance the overall long-term efficiency. The extensive simulation demonstrated that QL methods improved upon and ultimately outperformed the other, more conventional, baseline systems.

One of the main challenges to achieving 5G's goals and objectives is latency. Consequently, 5G needs to have the lowest possible latency. The latency issue in AmBC has also been considered, and the authors in [109] looked at latency issues in wirelessly powered AmBC systems from a deep QL perspective. First, a QL framework was developed for AmBC, and then, for the complex Q-network, a DNN was used, which proved to be more practical and effective. The findings demonstrated that the proposed work guaranteed low latency and high throughput.

To that end, RFID backscattering is a scalable and low-cost wireless technology. It uses energy harvesting methods to enable backscattering-based wireless power transfer. The flexibility of this resource allows for a wide range of potential uses. The authors in [110] presented the concept, framework, and ML methods underlying an RFID-based backscattering system. The algorithm for reading sensor tags and supply power was developed using several ML techniques, including SVM, ANN, and the Naive Bayes. Experiment-based evidence supports the provision of such methods. For example, the supervised SVM algorithm improves chipless RFID sensor tag reading capabilities because of the SVM method's exceptional signal classification performance. Comparatively, the magnetic WPT system with an ANN-based adaptive dynamic matching network achieves similar results across the entire WPT range. At the same time, a naive Bayes algorithm-based position estimation method for drones that receive their power wirelessly was presented.

The goal of this paper [111] is to use online design policies to improve the long-term average throughput

TABLE II: Summary of AI-based Solutions for BC Systems

Cat.	Ref.	Year	Source	Domain	Algorithm	Model Elements			Optimization Objective
						State/Input	Action	Reward/Output	
Backscattering Signal Detection and Channel Estimation	[96]	2017	Ambient RF	Clustering	Expectation Maximization (EM)	An ambient Backscatter system considers energy features of received signal	1.Explores the features of received signals directly. 2. Grouping of signals into clusters.	Improve performance	To assist signal detection without channel coefficients and noise power
	[97]	2020	Ambient RF	Classification	CRLD	1.RF signals with complications and are difficult to recover without CSI.	1. DTL detection framework utilizing offline learning, transfer learning, and online detection. 2. DTL-based Likelihood Ratio test. 3. CNN to explore signal features	Tag signal detection efficiently even without CSI.	Improve BER and Signal Detection performance
	[98]	2021	Ambient RF	Classification	CMNet-LRT	Various states and information of communication channel	Disable the partial layers and tune the remaining layers of the channel to fit the network to the current channel through transfer learning.	The improved tag detection performance with high throughput, utilizing only few training data.	Improve tag/signal detection capability conveniently
	[99]	2019	WiFi	Policy-Based	1.DRL-MAC, 2. DDQN	Consists of. WiFi signals from the WiFi Access Point(AP) and Backscattered Signals from the tag.	1. Tag Selection for Service, 2. Reservation Steps for the Tag	Compute Optimal Reservation Strategy	Tackle the over-optimistic estimation issue in Tag Detection
	[100]	2019	Ambient RF	Classification	SVM + Random Forest	Ambient signal types(WiFi, cellular) received	Classify received signals based on energy features.	An improved form of received signal with high efficiency.	Maximize the overall throughout by lowering BER
Jamming/Security and Interference Management	[101]	2019	Ambient RF	Policy-Based	DDNN Architecture	State consist of four elements. 1)State of RF Channel, 2)State of Jammer, 3)Number of Packets in Data Queue, 4)State of energy units	(M+4) Actions i.e, decide whether to stay idle, transmit data, harvest energy, backscatter data, adopts to transmission rate	Number of packets transmitted to gateways successfully	Find an optimal policy of maximizing the average long-term reward
	[102]	2021	Ambient RF	Policy-Based	Prioritized DDQL	State consist of four elements. 1)Channel state from previous time, 2)Deception status, 3)Number of Packets in Data Queue, 4)Total time of RARs	Six Possible actions to choose	Reward value is defined as a function of resulting SINR	Determine the optimal defense strategy using DRL-based method
	[103]	2021	Ambient RF	Policy-Based	Dynamic MDP + DDNN	State consist of four elements. 1)Deception status, 2)Jamming Status, 3)Number of Packets in Data Queue, 4)Number of energy units	Action space includes 1)Transmit data, 2)Harvest energy, 3)Backscatter Data, 4)Adopt transmission rate, 5)Stay Idle	Number of packets successfully transmitted	Determine optimal defense policy for the transmitter
	[104]	2019	Ambient RF	Policy-Based	MOGA	Optimization variables such as length, width, spacing, range, and so	Optimize Antenna parameters.	Reducing the number of large side lobes and side lobs level	to ensure security of IoT communication system, maintain communication quality, and leakage prevention
	[105]	2019	Ambient RF	Value-Based	QL	Power allocation states/status	Power allocation actions	Immediate reward based on SINR at each time interval	To improve the performance of backscatter networks particularly power allocation schemes in backscatter devices
	[106]	2019	Ambient RF	Value-Based	QL	State is represented as SINR	Determine time for backscattering and transmission power	Utility function of user and interferer time	improves the convergence speed of QL.
	[107]	2020	Ambient RF	Policy-Based	QL-reward function	State is based on Macro-Cell States and Small-cell States	Select transmission power level	Reward is computed based on corresponding SINRs	Effectively manage interference for legacy users and backscatter tags
Improvement in Throughput and Latency	[108]	2019	Ambient RF	Value-Based	QL	State is composed of battery energy and the channel gain	Determine whether to harvest energy or backscatter signal	Information amount transmitted successfully	Maximizing the throughput performance of backscatter systems by selecting operating mode.
	[109]	2020	Ambient RF	Value-Based	Deep QL	State is computed considering 1)other links interference, 2)the channel gain, 3)remaining data to transmit, 4)remaining time	Selecting a transmission power	reward function is based on the capacity of the link and the latency constraint	Tto overcome the delay constraints, while maximizing data rates and improving network performance
	[110]	2020	Ambient RF	Supervised	SVM + ANN	RFID based backscatter sensor system is presented.	1.SVM improves reading accuracy of sensor tags 2. ANN improves wireless power transfer system	Improves reading accuracy and communication range.	To improve reading capability of sensors.
	[111]	2021	Ambient RF	Value-Based	Value-Iteration	State consists of 1)data-link channel state, 2)battery state, 3)data queue state	five different actions to choose	Immediate reward is computed as throughput per block after decompression	Maximize long term average throughput.

of backscatter-based WPC systems. First, they drew a high-level diagram of the signal's life cycle, including sampling, encoding with compression, transmission, reception, and decompression and decoding. All these procedures are considered real-world issues like finite battery life, stochastic uplink channels, and a nonlinear energy harvesting model. High efficiency and gain were then attained through the MDP with hybrid switching mode, which allocated time and power and selected compression ratios to maximize efficiency. In an early attempt to find a perfect offline solution for this problem, the authors used the Value Iteration algorithm. Ultimately, they turned to the QL and Deep QL algorithms to find solutions online without prior knowledge. Simulation results demonstrate

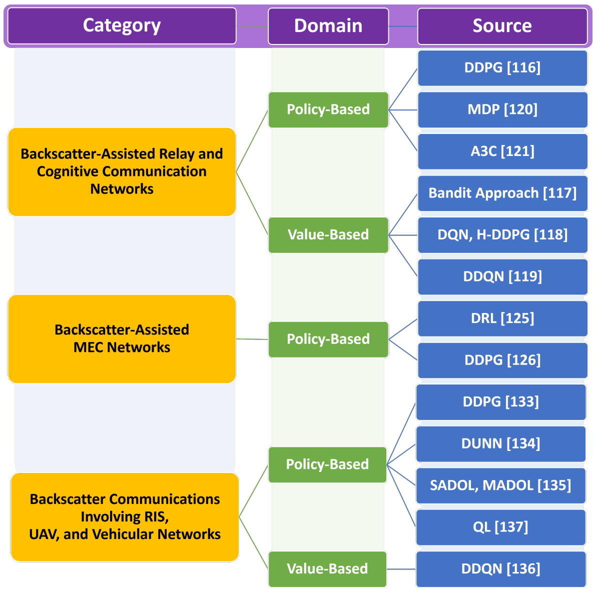

Fig. 8: Categories leveraging different AI domains and algorithms for BC based B5G/6G Technologies

that the hybrid transmission mode with adaptable data compression performs superior to the two baseline schemes (i.e., QL and random policy).

V. Exploring the Potential of AI-based Backscattering for B5G/6G Communications

BC is a rapidly evolving technology that holds tremendous potential to revolutionize the field of wireless communication and the Internet of Everything (IoE). Its unique capability of enabling devices to operate without relying on internal power sources has already significantly impacted various industries, including nanotechnology, UAVs, vehicular networks, and MEC network workload management. Moreover, BC has the potential to significantly enhance the performance of various networks, such as relays, cognitive radios, and MEC. However, the relationship between BC, RIS, UAVs, and vehicular networks presents opportunities and challenges for improvement.

This section provides a technical overview of these developments and highlights the impact of AI-based BC on wireless communication and IoT. AI plays a critical role in the advancement of BC technology. A comprehensive overview of AI-based solutions for BC, including the relevant domains and algorithms utilized, is presented in Fig. 8. At the end of this section, a comparative analysis of various schemes that leverage AI for BC in B5G/6G technologies can be found in Table III. This information is a valuable resource for individuals who aim to stay updated with the latest advancements in BC.

A. *AI-based Backscatter-Assisted Relay and Cognitive Communication Networks*

BC is a promising technology that has the potential to revolutionize communication networks. BC can be used in relay networks as an effective and low-power method of transmitting data between relay nodes, source nodes, and destination nodes [112] as shown in Fig. 9b. Furthermore, its low-complexity design enables energy-saving benefits for the network, as relay nodes can conserve energy when not transmitting data [113]. Similarly, in cognitive communication networks, BC can play a vital role in improving the utilization of available radio spectrum [114]. By reflecting existing signals in the environment to transmit data, BC reduces the need for dedicated transmission and frees up valuable spectrum resources for other communication systems, as shown in Fig. 9f. BC can also provide additional communication capacity in cognitive networks, especially in environments where the available radio spectrum is limited [115]. This sub-section will focus on AI schemes used for backscatter-assisted relay and cognitive communication networks.

In a Backscatter-assisted Relaying Network (BRN), D2D actively transmits data to receivers during a given time slot, while other D2D transmitters act as relays or helpers. Consequently, it improves the transmitters' data rate, energy efficiency, and transmission range. This method of relaying has been demonstrated to be effective, but a problem arises when these relays compromise the network's harvesting capability and thereby reduce overall performance. The authors in [116] have addressed the issue of compromising network harvesting capability in a BRN using DRL optimization methods. However, the dynamic energy states of the channel make it difficult for the Power Beacon Station (PBS) to find optimal solutions. To tackle this, the authors proposed the Deep Deterministic Policy Gradient (DDPG) algorithm as a solution. The DDPG algorithm finds the optimal solutions for the relays or helpers and addresses the PBS decision-making problem as a probabilistic optimization problem. The simulation results show that the proposed DRL scheme is more effective than conventional methods.

In a network powered by wireless devices, the transmitter requires more power to generate the RF signals due to its active transmission. One of the best solutions to this problem is to make the wireless devices operate in hybrid mode (active and passive) modes and to switch between two modes, i.e., active (wireless-powered communication network) and passive mode (ambient backscatter communication powered). In this paper [117], the authors suggested and presented an algorithm to switch between active and passive transmission modes. The authors first analyzed the hybrid relaying system and derived the analytical expression to check the end-to-end probability of success or failure. They have then leveraged the bandit policy to design a practical selection method where there is no need for network parameters but purely works on the past data or transmission records. Finally, the authors studied the selection problem for a hybrid relay that

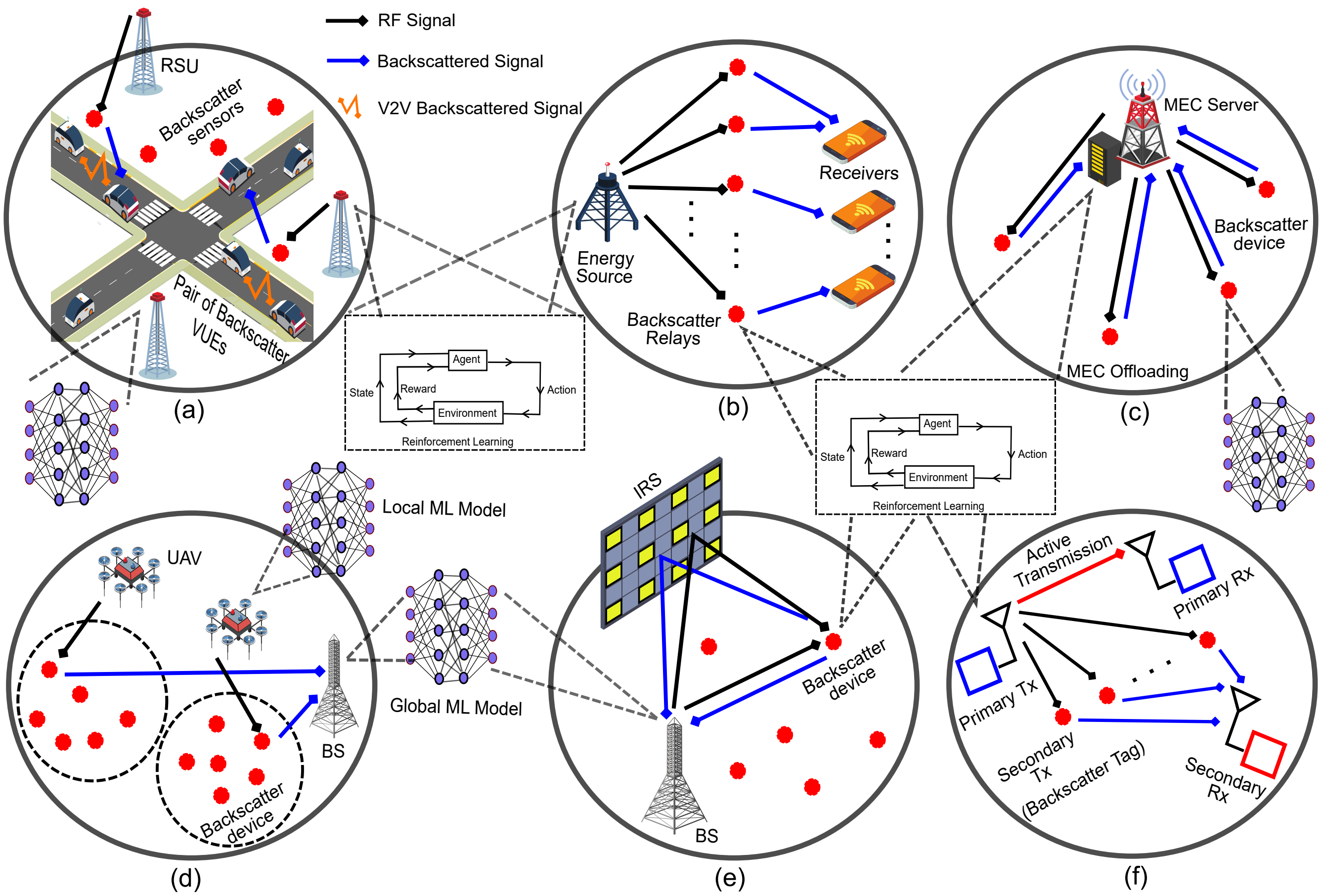

Fig. 9: Illustration of AI-based BC for B5G/6G technologies and networks, which include relays, cognitive radios, MEC, RIS, UAVs, and vehicular networks.

can work with hybrid wireless powered (Active mode) and ambient backscatter mode (passive mode). However, there is still a notable gap between the calculated and actual performance less practical. Therefore, further work can be done to make it more applicable.

The authors of this study [118] designed several wireless-powered relays to transport data or information from a multi-antenna AP to a single antenna location. These relays might function in active or passive modes based on channel parameters and energy states. In addition, they can operate in both modes but cannot deliver sufficient throughput due to mismatching or insufficient optimization. By optimizing both active and passive modes, optimal throughput can be achieved. Optimizing AP's beamforming with relays, combined radio modes, and other factors is the objective of this study, which aims to enhance overall performance. First, beamforming, additional relay modes, and the Hierarchical Deep Deterministic Policy Gradient (H-DDPG) algorithm are leveraged. It operates in such a way that it discards the selection of binary relay mode and transitions to a deep outer loop Deep Q-network (DQN) algorithm before acquiring optimization for continuous beamforming via the inner loop DDPG algorithm. Second, model-based optimization is integrated into the DDPG design by incorporating more accurate target recognition and DNN training to increase the system's ability to learn and train. Although the simulation results showed that the system appeared more feasible, the suggested algorithm is more sophisticated and can be further streamlined to be more helpful.

In the context of RF-powered backscatter cognitive radio networks, multiple secondary users communicate with a secondary-level gateway using backscatter or energy harvesting from RF signals. The gateway manages the backscattering, harvesting, and transmission time to prevent latency or congestion among multiple secondary users. The authors of [119] addressed this challenge by using a DRL-based DDQN algorithm to determine the optimal time scheduling policy for the gateway. The algorithm considers the hybrid Harvest Then-Transmit and backscatter techniques and optimizes the control policy for the sleep and active switching modes and the active mode reflection coefficient. Simulation results showed that the DDQN-based approach improves the system's throughput compared to benchmark schemes.

In another study, a simplified dynamic spectrum access architecture to enhance RF BC systems is proposed. After reflecting and gathering enough energy from environmental signals, a secondary transmitter in such a system then sends modulated data. In order to reach the optimal policy and optimize the system throughput, the authors of [120] decided to use the MDP for the ambient signals. Optimization based on MDP requires system parameters such as the probability of a channel being idle and the probability of correctly transmitted packets. However, these are elusive and cannot be obtained. With the authors' proposed online RL method, Secondary Transmitters (ST) can learn from their decisions and arrive at an optimal policy despite the lack of available channel characteristics. At the outset, the ST in the MDP framework establishes the action and state spaces in which an optimal policy can be found. The probabilistic matrix of transitions was then determined. Because MDP lacks context information, such as the odds of a channel being idle or a packet arriving, an online reinforcement algorithm was utilized instead. The controller does the action using the specified policy, observes the outcomes, and modifies the current policy. The iterative process helps the learning algorithm refine its approach. Simulation findings revealed that the suggested scheme is significantly more effective and efficient than previous benchmark schemes.

The increasing proliferation of wireless gadgets and sensor networks has necessitated the development of innovative communication techniques, such as BC. Despite BC's valuable benefits, wireless sensor networks have faced various challenges, particularly in resource allocation and the use of BC in mobile vehicles and UAVs. To address these challenges, the authors in [121] proposed a CR-based smart grid system that utilizes BC to improve resource allocation. The authors utilized a DRL-based A3C scheme to enhance system efficiency. The network architecture is based on two types of transmission: active transmission and ambient backscatter transmission. K-means clustering is applied as a pre-processing technique in a massively parallel setting. The algorithm prioritizes the output of high-priority users, enabling higher system throughput with fewer resources. Numerical results have confirmed the system's superior performance, demonstrating the feasibility and effectiveness of utilizing BC in wireless sensor networks.

B. AI-based Backscatter-Assisted MEC Networks

MEC technology provides low-latency processing and data storage at the edge of a network, closer to end-users. This enables various IoT applications and services, including augmented reality, video analytics, and edge computing [122]. BC can be combined with MEC to provide low-power and reliable communication for IoT and edge devices. BC can enable real-time processing and faster response times for IoT applications and services by transmitting data between IoT devices and MEC servers. In addition, BC can increase communication capacity for MEC systems, particularly in environments with limited radio spectrum availability.

Using BC in MEC networks can improve energy efficiency and communication reliability between edge devices and MEC servers [123]. BC enables edge devices to transmit data to the MEC server without active transmission, reducing energy consumption. Furthermore, integrating AI algorithms and ML techniques with BC can further enhance communication efficiency for IoT devices and MEC systems. Using BC and MEC, wireless networks can achieve efficient communication while minimizing the impact on other communication systems and preserving the available radio spectrum.

Furthermore, BC can be integrated with AI algorithms and ML techniques to provide efficient and effective communication for IoT devices and MEC systems, as shown in Fig. 9c. By leveraging BC and MEC, wireless networks can achieve efficient and effective communication while minimizing the impact on other communication systems and preserving the available radio spectrum [124]. Several studies have proposed AI-based BC-assisted MEC networks, which aim to optimize the performance of MEC networks by integrating BC into the network architecture presented in this subsection.

There are many entities in a network, each with a unique function and hence unique network service needs. Because of the increasing scale and complexity of the problem, optimizing wireless networks in this context is difficult. To improve the network's throughput, DRL can be used to train and raise awareness of the entities' decision-making capabilities in conjunction with their surrounding network environment. In this paper [125], the authors demonstrated how DRL could be utilized for MEC and used for user devices to offload computation workload to MEC servers. However, for low-power networks like wireless networks, MEC can be expensive due to its considerable power consumption during offloading. To address this issue, we develop a hybrid offloading paradigm that uses the complementing active and passive operations available in RF communications to reduce power usage. In this case, numerical findings demonstrated that a hybrid offloading approach was superior to more conventional efficiency improvement methods.

In a WPC network, devices opt to dump their tasks to the edge servers through active and passive backscatter transmission while consuming less or no energy. Multi-wireless devices integrated onto the same antenna can share the resources, i.e., channel. Therefore, work modes and time management for energy harvesting, backscatter active, and passive transmission should be appropriately managed to improve the overall system performance. In this work [126], the authors proposed a DDPG for the hybrid data offloading. By considering the best wireless devices, servers, and systems, try to find the best time in the consecutive domain to reduce network offloading delay. Moreover, DDPG complexity is analyzed, and the numerical results proved that approach could achieve minimal offloading delay and improve the energy harvesting efficiency. It is observed that wireless devices using the same channel and the same antenna may face scheduling problems and network transmission delays. DDPG-based scheme tackles this problem and reduces overall network offloading delay.

C. AI-based BC involving RIS, UAV, and Vehicular Networks

Integrating BC with B5G/6G technology is becoming increasingly vital in low-power communication and energy harvesting. One potential application of BC proposed is the creation of zero-energy devices, relying on power harvesting for functionality. RIS with many elements provides greater flexibility in balancing the trade-off between RF energy harvesting and information transmission [127]–[129] as shown in Fig. 9e. Moreover, the utilization of BC in UAVs is gaining prominence, particularly in remote sensing, environmental monitoring, and disaster relief [22], [130]. By enabling UAVs to communicate with ground devices without consuming battery power, BC increases these vehicles' energy efficiency and longevity, as shown in Fig. 9d, especially in environments where the line of sight between the UAV and ground device is obstructed. Similarly, BC offers a valuable solution in vehicular networks, enabling vehicles to communicate with each other and with RSUs in a more energy-efficient manner [131], [132]. By reflecting incoming radio signals, BC reduces energy consumption, extends communication range, and enhances network reliability. Furthermore, BC provides an economical solution for vehicular networks, requiring minimal hardware compared to traditional communication methods. Integrating BC into vehicular networks can improve traffic safety and efficiency through real-time information exchange between vehicles and RSUs, as shown in Fig. 9a. In this subsection, we will delve deeper into the AI schemes involving RIS, UAVs, and vehicular networks, highlighting BC's significant impact in promoting energy-efficient communication across multiple fields.

The authors in [133] have conceptualized an AmBC Systems assisted with the IRS. The optimization of IRS to aid AmBC is challenging due to the lack of past channel knowledge. Thus, the authors created a structure to synchronize the IRS and reader beamforming simultaneously, even when there is no channel coefficient and no CSI for the channel and ambient signal. The CSI deficiency and changing reward function in each interval were observed with independent training and zero discount factor. The authors have used the optimal eigenvector combiner with appropriate eigenvalues without IRS for better exploration. Based on their findings, the DRL framework can achieve competitive results with many full-CSI baseline schemes. In another study [134], the authors proposed a novel approach to design passive reflecting beamforming and symbol detection for an IRS-based AmBC system. The proposed approach uses a deep unfolding neural network (DUNN) model, which consists of two sub-networks: a phase shift design sub-network (PSDSN) and an expectation maximization detection sub-network (EMDSN). The PSDSN sub-network is responsible for designing the optimal phase shifts of the reflecting elements in the IRS. The EMDSN sub-network learns the backscattered symbols' BER model from training samples and detects the backscattered symbols by unfolding the expectation-maximization algorithm. The proposed DUNN model solves the constrained optimization problem by treating the optimization variables as network parameters. The study showed that the proposed DUNN model outperforms the random passive reflecting beamforming and AmBC systems without an IRS. However, further research is necessary to test the proposed approach's robustness and effectiveness in various practical scenarios.

The backscattering technique is a promising subject in communication, particularly in IoT. It allows sensor-based IoT networks to exchange data without needing continuous battery charge or replacement. As a result, wireless sensor networks can collect data from remote sites without recharging or battery maintenance. However, the limited range of backscattering is a challenge. To address this, the authors [135] proposed using multi-UAVs to assist in data collection. UAVs can fly near the Backscatter Sensor Nodes (BSN) to activate and collect data, reducing the average flight time of rechargeable UAVs during data collection. The authors used a clustering method, the Gaussian mixture model, to simplify the task and divide the BSNs into multiple clusters. Two algorithms were proposed, one for deterministic boundaries based on single-agent deep option learning (SADOL) and another for ambiguous boundaries based on multiagent deep option learning (MADOL). The results showed that the proposed algorithms outperformed others, such as MADDPG, DDPG, and Q network algorithms. Another paper [136] investigated the problem of energy efficiency in a BC network, where UAVs act as aerial BSs to improve system performance. The authors framed the optimization problem as an MDP. They proposed a DRL-based DDQN algorithm to design the UAV trajectory, considering constraints such as the scheduling of BDs, power reflection coefficients, transmission power, and fairness among BDs. Simulation results showed that the proposed algorithm achieved close-to-optimal performance and significant energy efficiency gains compared to benchmark schemes. The paper highlights the potential of using UAVs to improve the energy efficiency of BC networks in IoT applications.

Despite the growing user base and expanding coverage needs, heterogeneous networks are a great way to meet the capacity and coverage requirements of next-generation vehicular networks. However, the researchers cannot identify optimization opportunities for this class of networks. This study [137] proposed a learning method to deal with this optimization issue. The authors presented a strategy for resource allocation and user association for vehicle networks that consider collaboration-centric spectrum sharing. Network providers can serve the legacy and backscatter vehicular networks. Therefore, the challenges of power allocation, user association, and spectrum sharing are formulated to broaden the scope of network providers' utilization. Using DL approaches, the subsequent work increases the throughput of heterogeneous vehicle networks. A supervised RL method based on DL was presented for this purpose. In this method, DNN handled power allocation while QL was employed for VUE association and spectrum sharing.

TABLE III: Summary of AI-based BC Schemes for B5G/6G Communications

Cat.	Ref.	Year	Source	Domain	Algorithm	Model Elements			Optimization Objective
						State/Input	Action	Reward/Output	
Backscatter-Assisted Relay and Cognitive Communication Networks	[116]	2020	Ambient RF	Policy-Based	DDPG	State is comprised of energy transmission status, energy status, and energy storage capacity at time slots	Determine optimal reflection coefficients for helpers or relays, i.e., harvest or backscatter at each time slot	immediate reward is the signal transmitted at each time	Goal is to maximize overall network throughput over time slots
	[117]	2020	Ambient RF	Value-Based	Bandit approach	Hybrid relay system formulated as Bandit problem	Mode selection decision either action or passive mode	Higher reliability of data transmission.	Minimize unexpected accumulated regret
	[118]	2021	Ambient RF	Value-Based	DQN, H-DDPG	State is comprised of channel conditions and relay energy status	Time allocation and beamforming strategies	Optimize beamforming, time allocation and relay's parameters	To maximize overall throughput by jointly optimizing access point's beamforming and relay's radio modes and operating parameters
	[119]	2019	Ambient RF	Value-Based	DDQN	State is computed based on data queue status and energy status	Number of time slots selection (busy as well idle time slots)	Total number of packets transmitted in both modes	Find the optimal time scheduling policy for the gateway.
	[120]	2019	Ambient RF	Policy-Based	MDP	Channel state, energy level, data buffer status	Possible actions to choose are 1)Transmit data, 2)Harvest energy, 3)Backscatter Data, 4)Stay Idle	average throughput of the ST	Obtain optimal policy that maximizes throughput performance of backscatter and deals with dynamics of environment
	[121]	2020	Ambient RF	Policy-Based	A3C	State consists of data queue status, energy state, weight status, and occupation status	Action space consists of waiting, harvesting, backscattering and transmission decision on each time slot	Number of packets sent	Ensure maximum throughput of the multi-user backscatter system
Backscatter Ass. MEC Networks	[125]	2020	Ambient RF	Policy-Based	DRL	State is based on channel condition, energy status, and the workload status	Decision between local computation and the active offloading	Successful workload processed per unit energy	Learn the optimal hybrid MEC offloading policy
	[126]	2020	Ambient RF	Policy-Based	DDPG	State is based on wireless powered communication networks observation	Offloading decisions of every wireless devices	total offloaded data	Minimize the service latency and increase harvesting efficiency.
Backscatter Communications Involving RIS, UAV, and Vehicular Networks	[133]	2021	WiFi	Policy-Based	DDPG	It is computed as the combination of previous combiner and IRS reflection coefficients	selection of real and imaginary reflection components and combiners	improved detection performance at reader.	Facilitate further AmBC and improve its performance.
	[134]	2023	Ambient RF	Policy-Based	DUNN	Set of channel samples and training samples of backscattered symbols	Phase angle vectors of two RIS	Expectation maximization	To minimize the BER.
	[135]	2020	Ambient RF	Policy-Based	SADOL, MADOL	State is based on data collection ratios of BSNs, number of BSNs assigned to agent, set of UAVs locations	determine flying to the target, charge at the station, or collect the data	Reward is computed on energy, data collection, and the trajectory time	Minimize total flight time of rechargeable UAVs when mission is finished.
	[136]	2020	Cellular	Value-Based	DDQN	1.Energy efficiency problem for energy limited backscatter communication network 2. backscatter devices on ground harvest energy from wireless signal	1.reformulation of Energy efficiency maximization problem in an RL framework. 2. optimization of UAV trajectory jointly with reflection coefficients and fairness	gradually achieves significant energy efficiency.	To dealt with challenge of energy efficiency for UAVs.
	[137]	2021	Cellular	Policy-Based	QL	State is computed based on transmission power, channel gains, and harvesting energy capacity	allocate the number of resources	Amount of information transferred successfully at each time	To maximize the utility of Network Service providers.

VI. Open Issues and Future work

This section discusses several unresolved problems and challenges in BC and those aspects of backscattering that need further investigation and require significant attention. Future research must focus on flexible BC, considering multiple parameters such as intelligent jamming attacks, concurrent transmission, signal power, reflection coefficient, and energy conservation efficiency [47]. Despite this, the use of AI-based backscattering algorithms has been used to address several backscattering issues and challenges, such as signal recognition and channel estimates, interference and jammer management related to security concerns, difficulty in obtaining good throughput and minimizing latency in BC systems, and backscatter networks such as MEC networks, UAV and vehicle networks, etc. There are still some open issues to be tackled.

- **Heterogeneity of Ambient Signals:** The backscattering technique utilizes ambient signals for energy collection and transmission. However, these ambient signals have various origins and sources; as a result, they are unpredictable and challenging to explore. In addition, the backscatter receiver only recognizes familiar or trained signals. Therefore, there is a need for such algorithms or the development of an intelligent transceiver that can detect and utilize the many ambient signals that strike it to avoid this issue.
- **Interference to Licensed Systems:** Since backscattering occupies the frequency range of licensed users like TV and cellular BSs, it inevitably results in interference. Thus, these authorized users may experience signal weakening and distortion. Interference with licensed systems is a critical issue in BC systems, and several approaches can leverage to mitigate this issue. For example, BC systems can use adaptive techniques, cognitive radio techniques, advanced modulation, coding techniques, and regulatory measures to reduce interfer-

ence and maintain the quality of service for licensed systems. However, further research is needed to fully understand the impact of BC systems on licensed systems and develop efficient AI-based approaches to reduce interference.

- **BC Device Standards and Compatibility:** The network parameters used in backscattering are used for specific use cases and have proprietary features. For example, Flexible Macroblock Ordering (FMO) coding minimizes the energy consumption of multi-bit and BC devices to enhance the data rate. As a consequence, the backscatter devices become less interoperable and incompatible. Thus, it is compulsory to design communication standards and network protocols, e.g., packet format, network stack, and MAC protocol, for future AmBCs.
- **Security Challenges:** Since backscattering is based on a simple and easy-to-decode approach, the backscatter network is vulnerable to security vulnerabilities like eavesdropping and jamming [138]. Therefore, protecting a backscatter-based network is problematic because it is passive. Depending on the attacker's capabilities, the BC could be vulnerable to a denial-of-service attack, an impairment of the modulated backscatter, or even a complete compromise of the system due to the attacker's use of a backscatter network with more powerful and active transceivers. Furthermore, unlike encryption and digital signatures, backscatter transceivers do not seem to be able to provide any unique security solutions. As a result, extensive research needs to figure out how to fix the aforementioned security issues and come up with a straightforward yet foolproof method of protecting the BC network.
- **Network Standards and Protocols:** Using the WPN-BC system, a cluster of devices can be handled simultaneously, with a decrease in interference. However, the WPN-BC system should adopt new techniques that could simultaneously handle RF energy and BC. Specifically, the areas of decentralized MAC protocols should be explored more, where nodes talk in a distributed manner. Up to this, the coordination among the devices and tag selection are essential issues to be tackled.
- **Hardware Design Limitations:** Due to subsequent updates and modifications in WiFi and cellular networking, ambient signals have become more complicated. Thus designing AmBC systems has become a challenge due to the unpredictability and random nature of the existing network traffic and the hard fork to work in existing infrastructure with no or fewer modifications. Furthermore, the synchronization between transmission and reception is still a pending problem. The carrier phase and timing circuitry need a local oscillator, a power-hungry device. Thus, designing such a system with low complexity and high synchronization capability algorithms is highly desirable.
- **Integration of UAV with BC:** The integration of UAVs with BC networks has the potential to provide wireless connectivity in remote locations, aid in channel estimation and data transmission, and enable fast energy transfer. This paper discusses the basic parameters and problems of UAV-based BC networks using AI-based algorithms. However, more research is needed to fully integrate UAVs with WPN-BC and improve the performance of UAV-based networks. We also acknowledge the practical constraints of UAVs, such as scalability and mobility, and suggest that future research should explore ways to address these limitations. Nevertheless, by integrating UAVs with WPN-BC and enhancing their practicality, UAV-based BC networks can become a more valuable and reliable technology for wireless communication in remote locations.
- **AI-based Approaches:** The integration of AI with wireless networks, specifically with BC systems, can improve network performance, efficiency, and decision-making. In addition, AI algorithms can help address technical issues such as signal detection, interference management, and network optimization. This leads to improved performance and reliability in BC systems, enabling low-power and reliable communication for IoT devices and applications. However, more research is needed to fully understand AI's potential in BC systems.

  In 6G networks, AI-based BC systems can help achieve high spectral efficiency through adaptive modulation, coding, and frequency-domain resource allocation. Future research can focus on using AI algorithms to optimize network topology, link scheduling, and interference management.

  In mmWave and THz communications, AI algorithms can optimize the performance and reliability of BC. Similarly, AI-based backscatter VLC systems can improve the spectral efficiency, data rate, and power efficiency of VLC links. Finally, AI-based backscatter MIMO systems can enhance the performance of MIMO networks by optimizing modulation, beamforming, and link scheduling.

VII. Conclusion

This article comprehensively surveyed the current developments in AI-based BC. We covered different AI algorithms being utilized in the BC system, provided an introduction to BC, and then delved into the use of AI-based BC in various domains, such as detecting backscatter signals, estimating channels, regulating interference, and enhancing throughput and latency. We also discussed research into AI-based BC in the context of B5G/6G technologies, such as backscatter-assisted relay and cognitive communication networks, backscatter-assisted mobile edge computing networks, and BC incorporating elements like RIS, UAV, and vehicles. Finally, future work in the area of AI-based BC in B5G/6G networks could include developing AI algorithms for modulation and coding schemes, channel estimation, network management, hybrid communications, IoT applications, and security. These algorithms can optimize various aspects of BC performance, including spectral efficiency, error correction, data rate, network management, energy efficiency, and security. However, the specifics of these algorithms depend on the specific challenges and requirements of B5G/6G network environments.

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