Comprehensive Review on ML-based RIS-enhanced IoT Systems: Basics, Research Progress and Future Challenges

Sree Krishna Das, *Graduate Student Member*, *IEEE*, Fatma Benkhelifa, *Member*, *IEEE*, Yao Sun, *Senior Member*, *IEEE*, Hanaa Abumarshoud, *Member*, *IEEE*, Qammer H. Abbasi, *Senior Member*, *IEEE*, Muhammad Ali Imran, *Senior Member*, *IEEE*, and Lina Mohjazi, *Senior Member*, *IEEE*

***Abstract*—Sixth generation (6G) internet of things (IoT) networks will modernize the applications and satisfy user demands through implementing smart and automated systems. Intelligence-based infrastructure, also called reconfigurable intelligent surfaces (RISs), have been introduced as a potential technology striving to improve system performance in terms of data rate, latency, reliability, availability, and connectivity. A huge amount of cost-effective passive components are included in RISs to interact with the impinging electromagnetic waves in a smart way. However, there are still some challenges in RIS system, such as finding the optimal configurations for a large number of RIS components. In this paper, we first provide a complete outline of the advancement of RISs along with machine learning (ML) algorithms and overview the working regulations as well as spectrum allocation in intelligent IoT systems. Also, we discuss the integration of different ML techniques in the context of RIS, including deep reinforcement learning (DRL), federated learning (FL), and FL-deep deterministic policy gradient (FL-DDPG) techniques which are utilized to design the radio propagation atmosphere without using pilot signals or channel state information (CSI). Additionally, in dynamic intelligent IoT networks, the application of existing integrated ML solutions to technical issues like user movement and random variations of wireless channels are surveyed. Finally, we present the main challenges and future directions in integrating RISs and other prominent methods to be applied in upcoming IoT networks.**

***Index Terms*—6G, Reconfigurable intelligent surface, Machine learning, Deep learning, IoT, Resource management.**

I. INTRODUCTION

Fifth generation (5G) networks have been recently standardized and commercialized. Industry and academia have already started designing the next sixth generation (6G) communication system. Recent forecasts in [1-5] demonstrate that 6G systems will provide extraordinary efficiency by connecting a massive number of devices with humans, resulting in an extremely automated society and a data-driven universe through reliable and global wireless networks. Besides, several standard frameworks of 5G, i.e., massive ultra-reliable low latency communications (mURLLC) and ultra-massive machine type communications (umMTC) [4], among others, need continuous development for internet of things (IoT) applications to the next generation. Aiming to achieve the highest key performance indicators (KPIs) 6G networks are expected to be able to self-protect, self-heal, self-optimize, self-organize, self-plan, and self-manage their resources [6-8] through adopting the network activities and functions according to energy constraints, network usage, environmental status and so on. Table I demonstrates the KPIs of 6G systems relative to 5G. Deploying these technologies on a single platform is considered a challenging task, especially that their stringent requirements, in terms of trustworthiness, data rate, and latency, need to be met simultaneously.

TABLE I
COMPARISON BETWEEN 5G AND 6G [9].

Network features	5G	6G
Data rate	10 $Gbps$	1 $Tbps$
Mobility	10 $Mb/s/m^2$	1 $Gb/s/m^2$
Connection density	10^6 $devices/km^2$	10^7 $devices/km^2$
Latency	1 ms	10-100 μs
Coverage percentage	Around 70%	Greater than 99%
Energy efficiency	100x comparative to 4G	10x comparative to 5G
Spectrum efficiency	About 3-5x comparative to 4G	About 3x comparative to 5G

As beyond 5G (B5G) desires for innovative standard moves, current wireless technologies such as LTE-A system, multiple-input multiple-output (MIMO), etc., demand more energy and processing resources which might be affected by the lousy transmission environments [3]. Another technology that can overcome the undesired influence of the environment is the relay communication technology, which requires more hardware consumption and complex signal processing [5]. As a

S. K. Das is with the Department of Electrical, Electronic and Communication Engineering, Military Institute of Science and Technology (MIST), Dhaka-1216, Bangladesh (e-mail: skshna@yahoo.com).

F. Benkhelifa is with the School of Computing, Electronics and Mathematics, Coventry University, Coventry, CV1 2JH, UK. (e-mail: ad8904@coventry.ac.uk).

Y. Sun, H. Abumarshoud, Q. H. Abbasi, M. A. Imran and L. Mohjazi are with the James Watt School of Engineering, University of Glasgow, Glasgow, G12 8QQ, UK. (e-mail: Yao.Sun@glasgow.ac.uk, hanaa.abumarshoud@glasgow.ac.uk, qammer.abbasi@glasgow.ac.uk, muhammad.imran@glasgow.ac.uk, l.mohjazi@ieee.org).

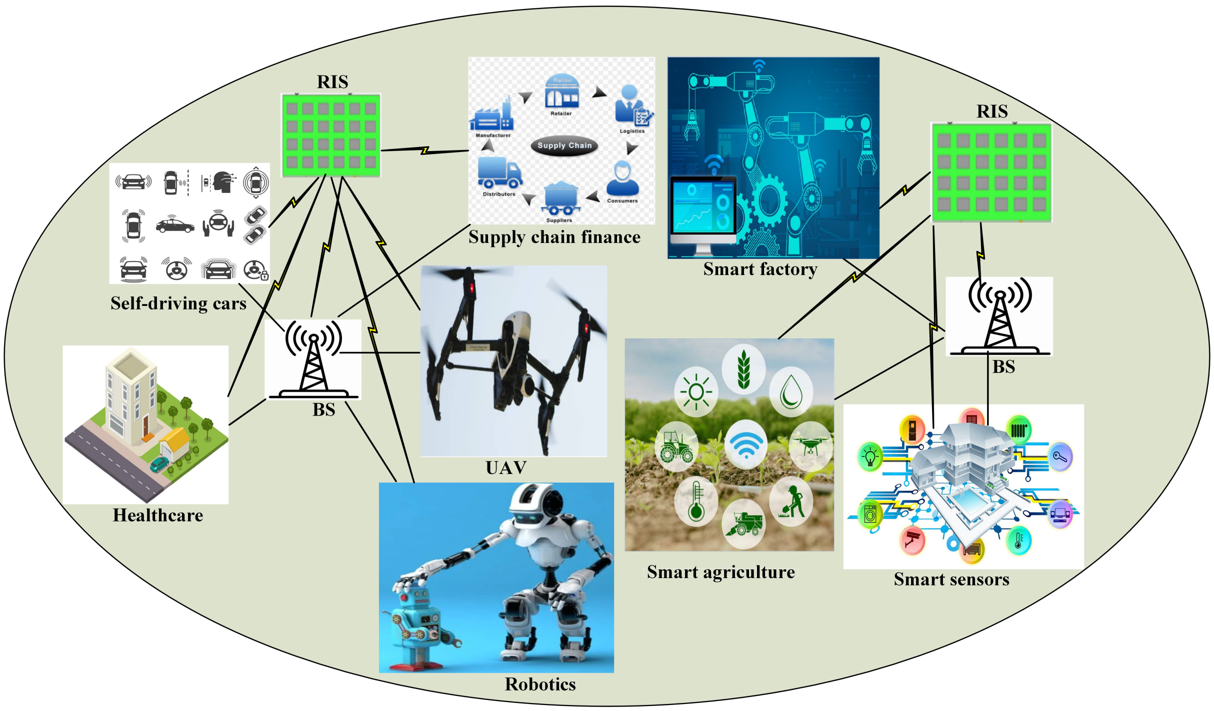

Fig. 1. ML for intelligent IoT applications using RIS.

result, reconfigurable intelligent surfaces (RISs) are recognized as an economical and green technique capable of offering significant enhancement in terms of energy and spectrum efficiencies [10-13]. In addition, a simultaneous access method empowered by RISs to boost the system performance for IoT networks, consequently designing a communication-efficient framework is crucial for 6G IoT networks. Due to their reconfigurability, RISs are seen as an auspicious solution to support the IoT system design and optimization by facilitating channel modeling, signal, and acquisition which allows smart wireless environments useful to 6G based applications.

RIS technology allows a number of promising applications like multiple-input multiple output (MIMO) communications [10], terahertz (THz) communications, and non-orthogonal multiple access (NOMA) communications in the context of 6G-IoT networks. Technological emergence and recent public trends are combined with the enormous increase of machines for shaping numerous advanced IoT-aided services, for example related self-regulating artificial intelligence (AI) systems, holographic telepresence, flying vehicles, telemedicine, augmented reality (AR), and virtual reality (VR) using machine-to-machine (M2M) communications [16-18].

A. Motivation

Utilizing the potential of control, computation, communication and sensing, the IoT is assumed to provide automatic data transmission facilities and connect about 50 billions of user equipments (UEs) globally by 2030 including sensors, smart phones, etc. [9]. Furthermore, the recent advances in machine learning (ML) create a perfect tool to analyze the traffic delay and reliability for enabling mURLLC in 6G-IoT, by offering tremendous solutions, such as precise traffic and mobility prediction. The use of ML becomes more important when the IoT network information is lacking, such as channel state information (CSI) or received pilots, and the cellular network environment is extremely dynamic. The concept of the next-generation communication network creates the opportunity to design an intelligent network with RIS in the paradigm of IoT to process large data, which is called an intelligent IoT system striving to create a controllable, intelligent, reconfigurable, and programmable radio propagation environment. ML can generate necessary information from a huge volume of data produced by various IoT devices resulting in RIS enhanced intelligent IoT facilities, such as supply chain finance [18], healthcare, robotics, intelligent factory [19], unmanned aerial vehicles (UAVs) [13], intelligent wireless sensor networks [12], self-driving cars [13], etc. Smart agriculture is an emerging concept that refers to managing farms using RISs to increase the quantity and quality of products while optimizing the human labor required which is shown in Fig. 1, where the RIS can be installed on the building. The driving force of smart farming is IoT connecting in smart machines and sensors integrated with RIS on farms to make farming processes data-driven and data-enabled. Various technologies like ML empowered intelligent IoT systems are helping humans to get their tasks done with the least effort. The application of intelligent IoT systems have helped the farmers in a wide range of activities, such as monitoring the water levels in tanks, monitoring the climate condition, precision farming, livestock monitoring, and so on. Fig. 1 represents the ML-based intelligent IoT network using RIS which facilitates various intelligent sectors and is formed by the base station (BS) at the midpoint of a cell and a number of IoT devices around it. The above-mentioned benefits turn ML into a promising technique by utilizing communication and computation resources for distilling intelligence directly at network edge, thus unleashing the full potential of ML in a plethora of thrilling intelligent 6G-IoT applications.

B. Related works

The existing surveys [1], [4]-[8], [15], [18]-[19], [21]- [22], short magazine papers [2], [11], [14], [20], [25] and tutorials [12], [17], [23] discussing RIS and its variations, focus on various aspects for 6G wireless communications. Di Renzo et al. in [18], Q. Wu et al. in [24] and C. Liaskos et al. in [25] spotted some barriers and forthcoming research scopes by investigating several RIS-aided applications which work as reflectors in radio communication networks. Besides, a summary of reflective wireless technology was represented by Y.-C. Liang et al. in [17] particularly focused on big intelligent surfaces or antennas. Moreover, L. Subrt et al. in [26] introduced the concept of an intelligent wall as an autonomous part of a smart indoor environment for cognitive wireless networks. RISs are implemented using different technologies in B5G communications which are described in the following below.

E. Basar et al. in [1] and M. Di Renzo et al. in [21] described the fundamental differences between reconfigurable metasurfaces (RMSs) and other technologies using mathematical techniques and elaborated on the potential use cases of RIS in 6G. S. Hu et al. in [27] proposed a system for positioning in which antenna arrays were deployed as an RIS using Fisher information matrix (FIM) and Cramer-Rao lower bound (CRLB) schemes. X. Tan et al. in [28] analysed the millimeter-wave (mmWave) frequency band by utilizing the reconfigurable 60 GHz reflect-array which minimized the link failure outage probability. C. Liaskos et al. in [29] proposed a software-programmable wireless environment, based on programmable metasurfaces which improved the system performance in 2.4 GHz and 60 GHz frequencies. G. Yang et al. in [30] proposed an RIS-assisted NOMA system by jointly optimizing the power allocation and the phase shifts using descent and semidefinite relaxation techniques which enhanced the rate performance significantly. E. Basar et al. in [31] proposed an RIS-assisted communications system using the index modulation (IM) which provided the highest data rate as well as ensured the lowest error rate. M. Jung et al. in [32] proposed the uplink data rate in an RIS-based large antenna-array system where the estimated channel on RIS was subject to estimation errors, interference channels were spatially correlated Rician fading channels, and the RIS experiences hardware impairments which improved reliability and a significantly reduced area for antenna deployment. S. Zhou et al. in [33] analyzed an RIS-assisted multiple input single output (MISO) downlink system with hardware impairments using hybrid beamforming optimization algorithm which improved the energy efficiency (EE). Q. Wu et al. in [34] proposed an RIS-aided cellular network by jointly optimizing the continuous transmit precoding and the discrete reflect phase shifts using both optimal and suboptimal algorithms. J. Zhu et al. in [35] proposed a zero-forcing beamforming based RIS for downlink MISO NOMA transmission scheme, which achieved better performance than orthogonal multiple access. The aforementioned discussion appraised key research works in the field of RIS along with their used schemes and functionalities. While 5G is yet to be realized fully, the researchers have already started looking for energy and spectral-efficient solution for intelligent IoT applications in 6G by controlling the radio propagation.

C. Huang et al. in [19] explained holographic MIMO surfaces (HMIMOS) communications which are capable of impacting electromagnetic (EM) waves according to desired objectives. N. Kaina et al. in [36] proposed controlling light propagation by using electronically tunable metasurfaces in reverberating environments with non-coherent energy feedback. H. Yang et al. in [37] described a real-time switch for future IoT applications which were achieved by using a field-programmable gate array (FPGA). L. Zhang et al. in [38] proposed digital coding metasurfaces to obtain simultaneous manipulations of EM waves in both space and frequency domains, i.e., to control the propagation direction and harmonic power distribution simultaneously. As per [12], [14], during the design selection of the recent IoT systems, a number of barriers were found which were expected to be removed by developing a traditional system that would work on the nodes in a radio propagation atmosphere. This paper aims to review the up-to-date research works on intelligent IoT networks, for finding the major dissimilarities with backscatter or relay aided communication methods, overcoming the highest significant open investigation problems, and highlighting the reasons to use the RISs by inspecting the recently deployed communication-centric designs in IoT networks.

The joint optimization of the RIS's phase control and the transceivers' transmission control in different network design problems, e.g., rate maximization and power minimization problems which highlighted important practical challenges and future research directions for realizing intelligent IoT networks in B5G communications are discussed in [22]. ML oriented systems have great importance in RIS-employed radio communication networks due to the capability of managing non-convex and high-dimensional optimization problems [8]. Particularly, we will focus on the potentiality of RIS usage in order to shape radio links and realize IoT networks using AI algorithms.

In [20], authors introduced Wireless 2.0 by leveraging the emerging technologies of RMSs and updated deep learning (DL) algorithm as well as other ML-based approaches in radio communication, providing significant performance improvement in numerous applications. For offline training of the introduced deep neural networks (DNN) model in [39], appraised channel information from some active RIS components work as input for predicting the best RIS reflection beamforming matrix. Besides, while avoiding the transitional

TABLE II
COMPARISON OF THIS WORK WITH AVAILABLE MAGAZINES/SURVEYS/TUTORIALS.

Ref.	Year of publication	ML approach	Key contributions	Limitations	Related contents in this work
[8]	2021	DL	Requiring fewer data in the training phase compared to the benchmark method	Labeling requires heavy computation resources	Section III
[12]	2020	FL	Reduces the model aggregation error	Higher computational complexity	Section III
[14]	2021	SL, USL, RL, and DNN	ML-empowered real-time deployment of RISs for IoT networks	Lack of information of ML-assisted resource management policy for intelligent IoT systems	Section V
[15]	2020	RL	Provides standalone operation since RL doesn't require labels like SL	Requires active RIS elements for channel acquisition	Section V
[40]	2020	DNN	Comparable performance with the SDMs	Only optimal RIS passive beamforming is provided	Section III
[43]	2019	USL	No need for channel estimation	Needs to design beamformers and require huge datasets and DNN architecture	Section III
[45]	2020	DRL	RIS works without requiring any prior training overhead	Does not predict the optimal RIS reflection beamforming matrix at the offline training phase	Section III
[47]	2020	FL	Less transmission overhead for training	Performance depends on the number of users and the diversity of the local datasets	Section III
[48]	2020	Multilayer perceptron (MLP)	Accelerated convergence thanks to local model updates	Only RIS-beamforming is accomplished	Section III
[49]	2020	DNN	Leverages both ML and DL methods	Requires active RIS elements	Section III
[50]	2019	Q learning algorithm	Only suitable for scenarios with small state space and action space	Can find the optimal policy without requiring knowledge about the environment	Section V
This paper		DRL, DNN, FL and FL-DDPG	An extensive survey on the ML-based RIS-assisted IoT system. Particularly, • Detailed analysis of DRL based on resource management in RIS enhanced IoT networks. • Detailed analysis of DNN-based multi-user M2M communications and future research directions. • Intelligent IoT networks and in-depth review of the FL-based solutions in multiple domains. • FL enabled the DDPG framework to jointly optimize the deployments, phase shifts of RISs, and the power allocation policy for UEs using RIS which reduces the training time.	Analysis of the DRL, DNN, FL, and FL-DDPG with emerging technologies, while other domains (e.g., IoT services), such as attack detection, integrated sensing, and communication are not discussed.	

phase of channel approximation, the presented methods in [40] and [41] that use received pilots as input to train the proposed DNNs to predict the optimal RIS phase shifts and beamforming vector at the BS. Also in [42], authors investigated an offline training enabled DNN model which was capable of learning the inherent association among the optimum RIS organization and estimated receiver (Rx) coordinates. Aiming to get rid of the considered data collection overhead in setting of supervised learning (SL), the researchers in [43] proposed an RIS beamforming feedforward neural network (RISBFNN) model using unsupervised learning (USL) and reinforcement learning (RL) methods for shaping the phase shift properly where the measured links at BS and avoided transmission rate act as the input and loss function respectively. Furthermore, deep reinforcement learning (DRL) is another ML technique that uses online data collection based training approach and increases throughput by optimizing problems in different radio network circumstances [44].

C. Huang et al in [15] presented an actor based DRL method for exploring the combined architecture of the RIS phase shift shaping and transmit beamforming matrix at BS for multiuser MISO application. Besides, A. Taha et al. in [45] proposed a DRL based intelligent self-regulating RIS system for determining the best RIS beamforming vector. In addition, G. Lee et al. in [46] was studying a DRL-aided design for maximizing the mean EE via empowering the BS to control the suitable transmission power and finest RIS arrangement. As per Table II, the existing works still exhibit some limitations which are explained in this survey paper. The limitations are listed below:

- Resource management techniques were not highlighted as one of ML based application for RIS-enabled systems in several current surveys. Most works concentrate on other ML-based aspects, such as traffic management, data

aggregation, clustering, scheduling, security, architecture, use-case and so on.
- Deep RL algorithms were not considered in intelligent IoT networks. Mostly, they study ML approaches such as SL, recurrent neural networks (RNN), convolutional neural networks (CNN) etc.

Although the aforementioned magazines/surveys/tutorials analyzed basic concepts of RIS, which lack the modification of the radio propagation environment in existing 5G cellular networks, future 6G wireless networks may have the perspective of shaping for realizing the intelligent wireless propagation environment and intelligent wireless resource management towards their liking. To overcome the aforementioned problems, this paper describes ML-based resource management for IoT networks. Besides, we present an ML-assisted method for learning the channel variation features in the communication atmosphere among user devices. After learning once, the ML structure will be able to adopt the links over the RIS panel shaping according to the atmosphere. Deprived of depending on unambiguous channel appraisal, this structure facilitates controlling RIS components and other RIS-assisted systems optimally. Therefore, overcoming the present limitations by sealing the research cracks is the main contribution of this paper which particularly provides a complete survey on the ML-oriented IoT applications. As the combination of ML procedure and the intelligent IoT networks are needed according to our observation, hence we propose a communication principle-enlightened characteristic plan to support the developed DL model by learning the essential interactions and atmospheric features more proficiently.

C. Contributions and structures

Inspired by the RIS potential to realize IoT networks using ML algorithm and its compatibility with other technologies, the main contributions of this study can be summarized as follows:

- We present the intelligent radio propagation architecture and the benefits of ML-based intelligent IoT networks.
- We review the major principles governing the RIS functionalities as well as their communication with EM waves. We also analyze the usual SDMs roles and highlight their potential applications and associated practical challenges.
- We explain the necessity of combining RISs and ML. Considering the intelligent radio communication system, we discuss various ML-integrated schemes, such as DRL, DNN, FL, DDPG, and FL-DDPG techniques to design the native propagation atmosphere except depending on unambiguous channel approximation. The essential characteristics of the designed atmosphere will be reflected by the trained model resulting in optimum RIS shaping prediction in a particular circumstance.
- We present the incorporation of promising technologies for ML-based intelligent IoT networks, such as physical layer security (PLS), UAV, cognitive radio (CR) networks, simultaneous wireless information and power transfer (SWIPT), simultaneously transmitting and reflecting reconfigurable intelligent surface (STAR-RIS), NOMA, vehicle-to-vehicle (V2V) communications, backscatter communications, THz and optical communications.
- We explore RISs according to the data-driven viewpoint and accordingly evaluate the spectrum allocation and beamforming-based joint schemes for IoT networks, comprising their restrictions which direct the integration of ML techniques.
- We identify the main research scopes regarding the RIS-ML and other promising techniques based on IoT networks for proposing further potential solutions for the full realization of intelligent IoT networks.

TABLE III
LIST OF ACRONYMS AND THEIR DEFINITION.

Acronym	Definition
RIS	Reconfigurable intelligent surface
SDMs	Software define metasurfaces
FPGA	Field programmable gate array
CMOS	Complementary metal oxide semiconductor
EM	Electromagnetic
RF	Radio frequency
MEMS	Micro electrical mechanical system
PL	Path loss
NLOS	Non-line-of- sight
LoS	Line of sight
Fifth generation	5G
Sixth generation	6G
Transmitter	Tx
Receiver	Rx
CSI	Channel state information
ML	Machine learning
AI	Artificial intelligence
DL	Deep learning
RL	Reinforcement learning
FL	Federated learning
DQN	Deep Q-networks
DRL	Deep reinforcement learning
DNN	Deep neural network
DDPG	Deep deterministic policy gradient
QML	Quantum machine learning
CNN	Convolutional neural network
IoT	Internet of things
M2M communications	Machine-to-machine communications
V2V communications	Vehicle-to-vehicle communications
STAR-RIS	Simultaneous transmitting and reflecting reconfigurable intelligent surface
UAV	Unmanned aerial vehicle
PLS	Physical layer security
SWIPT	Simultaneous wireless information and power transfer
SINR	Signal-to-interference-plus-noise-ratio
MIMO	Multiple input multiple output
MISO	Multiple input single output
FD	Full duplex
BS	Base station
eNB	Evolved node B
QoS	Quality of service
SE	Spectrum efficiency
EE	Energy efficiency

Fig. 2 shows the anatomical organization of this survey. The rest of this paper is organized as follows. Section II discusses the benefit of intelligent IoT systems and the architecture as

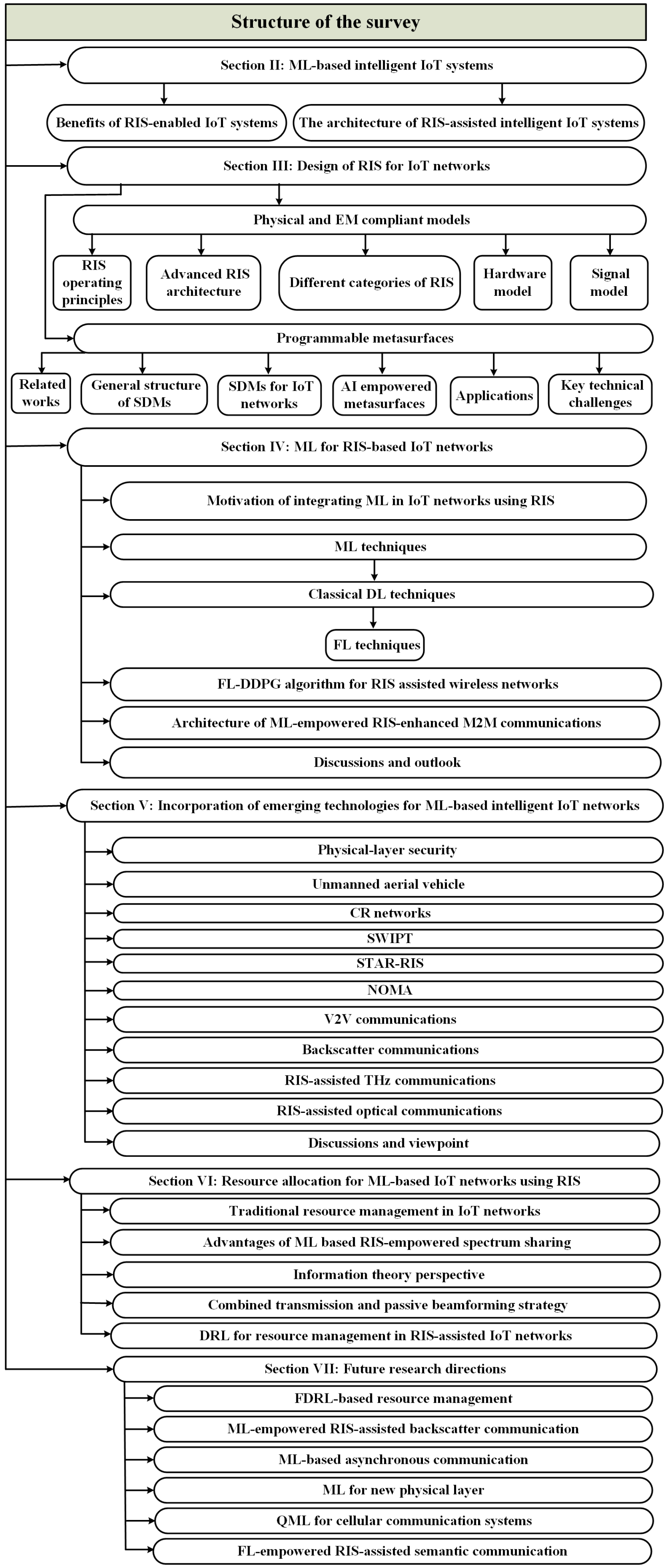

Fig. 2. The anatomical organization of this survey.

well as the convenience of ML-based intelligent IoT networks. The basic concepts, fundamental characteristics, classification, operational principle of RISs and wireless functionalities of SDMs for IoT networks are presented in section III. The inevitable trend of RIS combined with ML is also thoroughly elucidated in section IV. Integration of RIS with emerging technologies are elaborately discussed in section V. Resource allocation for IoT networks using RIS is expounded in section VI. Then, the challenges and potentials related to the topic are provided and discussed in section VII. The conclusions are summarized in section VIII. Finally, Table III lists the mostly utilized acronyms in the manuscript for the convenience of the readers.

II. ML-based Intelligent IoT Systems

In this section, we discuss the benefits of RIS-enabled IoT systems. The architecture and advantages of ML-based intelligent IoT networks are also presented.

A. *Benefits of RIS-enabled IoT systems*

The enhancement of EM metacomponents [13] turned RIS into an interesting research topic in the last few years because of its exceptional EM wave controlling features which makes it a vital mechanism for intelligent realization of the propagation atmosphere for IoT networks. The benefits of intelligent IoT systems are mentioned below:

- **Simple installation:** RIS is almost passive device which is prepared from EM components, i.e., amplitude, frequency and phase. It can be installed on numerous structures, such as indoor walls, building facades, vehicle windows, highway polls, roadside billboards, aerial platforms, pedestrians' clothes and so on because of their lower price.
- **Transmission power reduction:** The improved channel situation also indicates that the sender device can reduce its transmission power while upholding the similar signal quality level during delivering data to the destination resulting in a higher energy-efficient communication model. RIS works in unnatural properties way, such as negative refraction, perfect absorption, and anomalous reflection [14]. Furthermore, the spatial feeding scheme of RISs avoids the excessive power loss caused by the bulky feeding networks of phased arrays. Consequently, RISs considerably reduce energy consumption. The power scaling rule shown in [7] indicates that the BS's transmission power in an RIS aided network can be reduced by the order of $\frac{1}{N^2}$ [13] except damaging the receiver's efficiency, where N means the amount of the RIS's scattering components. A similar power scaling rule also grips for a real-time RIS with small phase resolution. In addition, the power reduction is more important to those users who are in long distance from the BS [13].
- **Resource efficiency (RE) improvement:** RIS can reconfigure the radio propagation atmosphere by compensating the power loss in long distance communications. Passive reflection impacting radio waves can create wireless line of sight (LoS) channels between mobile users and BSs. But they cannot avoid obstacles, such as high-rise buildings degrading the signal quality. The design and implementation of intelligent RIS can build a software programmed radio transmission atmosphere that improves the received signal-to-interference-plus-noise ratio (SINR). Thus, we can conclude that RIS passive reflection adds power gain, which can be either utilized to improve the system throughput and reduce the power consumption.
- **Environment friendliness:** Through controlling the phase shift of every reflecting component in the place of using a power amplifier [19], RIS can shape the receiving signals compared to traditional relaying methods, such as decode-and-forward (DF) [6] and amplify-and forward (AF). Hence, utilizing RIS is more environmentally friendly and energy-efficient compared to traditional DF and AF systems. Besides, software defined metasurfaces (SDMs) usage utilizes the intelligence without the expectation of new signal generation that makes them promising for decreasing the EM radiations and utilizing in various systems in airplanes, hospitals, etc.
- **Compatibility:** RIS permits full-band and full-duplex (FD) propagation because of reflecting only EM signals. Furthermore, intelligent IoT networks fit with the hardware and standards of current radio networks [13]. As RIS holds the above-mentioned features, it is considered as a proficient technique to mitigate challenges in civilian and commercial applications. Several existing researchers study RIS based application setups using various assumptions which propose distinct system architectures.

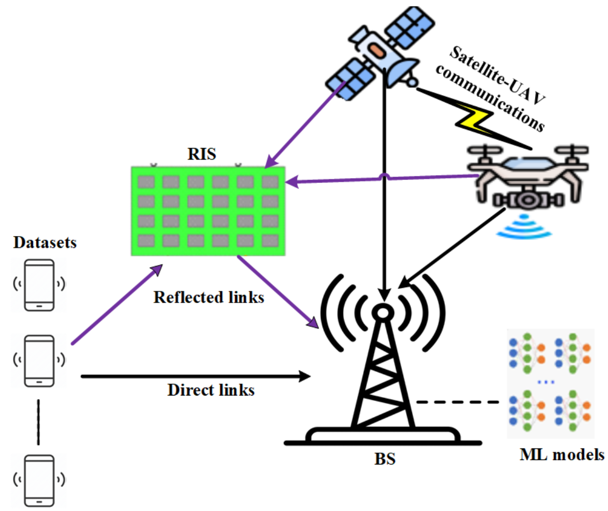

Fig. 3. ML-based intelligent IoT network.

B. *The architecture of RIS-assisted intelligent IoT systems*

RIS-assisted ML system model for IoT networks is presented in Fig. 3. We assume a scenario where a BS is surrounded by N number of IoT UEs. Every UE performs a ML

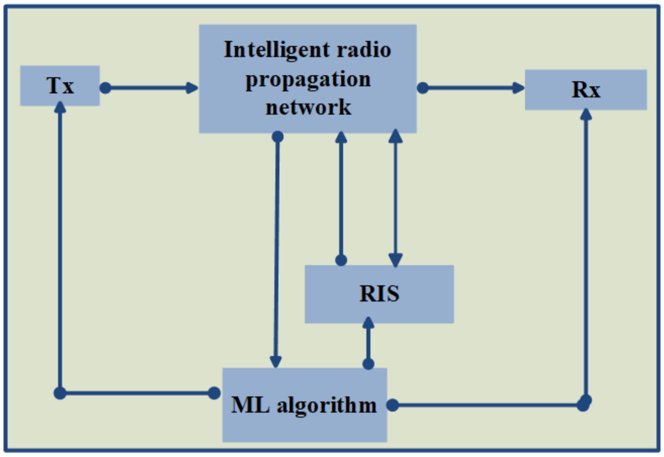

Fig. 4. Paradigm of configuring an intelligent radio propagation environment.

task. M amount of passive reflecting components switch the phases of incident signal waves form an RIS which assists the entire network. Especially, the BS is responsible for training k categorization models through the trained data collection from N mobile users. While carrying the training data to BS from the mobile users, wireless channels expose intrinsic random characteristics because of multi-path issues and experience a large amount of propagation loss [23]. Communication from the transmitter (Tx) to Rx can be done using non-line-of-sight (NLoS) or LoS wireless channels. In this paper, we consider an RIS aided method for intelligent channel configuration to enable the realization of a smart wireless environment, explained from shallow to deep perceptions. While using RIS, the channel among the N users and BS utilizes the reflected link (user-RIS-BS link) and the direct link (user-BS link) wherein the reflected link includes RIS-BS line, phase shifts at RIS and user-RIS link. An ML-oriented designing technique is presented in this paper which elucidates from the intelligent radio structures and systems of metamaterials to the ML-enhanced RIS-based cellular networks. During the development of RIS enabled elements, the advancement of ML, RL and DNN algorithms have facilitated various areas like computer vision, robotics, etc.

With the inherent restrictions of terrestrial environments, non-terrestrial networks are envisioned as an enabling technology for ubiquitous connectivity in future IoT applications. Non-terrestrial networks including such platforms as UAVs, high altitude platform stations (HAPS) nodes, and low earth orbit (LEO) satellites are capable of addressing such challenges as blind spots, coverage holes, sudden rises in throughput demand, and terrestrial network failures. In the above-mentioned scenarios, accurate channel estimation with a small pilot overhead is a crucial challenge to both UAV-satellite links and air-to-ground links over dynamic wireless channels due to the satellite orbiting and UAV three-dimensional (3D) trajectory. Moreover, integration of RIS in satellite communication can appropriately control various channel conditions, minimize path loss (PL) exponent and improve EE resulting in flexible data transmission among the satellites which are located at same/different orbits. As the scattering components are huge in size, the passive beamforming turns difficult. Because this technique does not demand received pilots and CSI which creates large computational complexity. Consequently, the designing issues of ML enhanced signal processing methods in order to control RIS in real-time is of superior significance. In this survey paper, we aim to explore the impact of ML while outlining effective methods for controlling real-time RIS. The methods for the implementation of ML integrated RIS models are explored, analyzed and overviewed considering 6G radio networks. Because of the proactive shaping ability of radio communication atmosphere, RIS has been a crucial research topic for mitigating numerous complexities faced in assorted IoT based radio communication networks [23]-[24]. The paradigm of ML-based configuring an intelligent radio propagation environment is shown in Fig. 4. Due to playing a significant role in many RIS-enabled intelligent IoT systems, the conveniences of ML-based intelligent IoT networks are given below:

- **Conserving data safety and device confidentiality:** Except for sharing the gathered information among the BS and the IoT devices, the raw data of every IoT device is not revealed to other devices and the main server. Therefore, ML promises the data secrecy and device confidentiality in intelligent IoT systems. Following the progressively stringent data secrecy protection legislation, such as the General Data Protection Regulation (GDPR), the ability of guarding user information of ML is important for constructing sustainable and safe intelligent IoT systems [12].
  ML detects threats by constantly monitoring the behavior of the network for anomalies. ML engines process massive amounts of data in near real time to discover critical incidents. These techniques allow for the detection of insider threats, unknown malware, and policy violations. Hence, double authentication private-preserving analysis is integrated with GDPR scheme to guarantee the accessibility of transaction data, data providers' secrecy, and fairness between information providers and information customers.
- **Supporting joint training:** Joint ML is able to combine the computation resources and the gathered information over a big amount of scattered IoT devices for cooperatively constructing a ML empowered intelligent IoT architecture. Consequently, every device attains an improved ML based intelligent IoT architecture compared to the individual achieved model. Furthermore, this cooperation would accelerate the convergence rate of the whole data training procedure and increase learning accuracy [12].
- **Decreasing network delay:** Deprived of demanding the IoT devices to upload the massive volume of training data to the system, ML enhanced intelligent IoT architecture eliminates the weighty communication burdens and

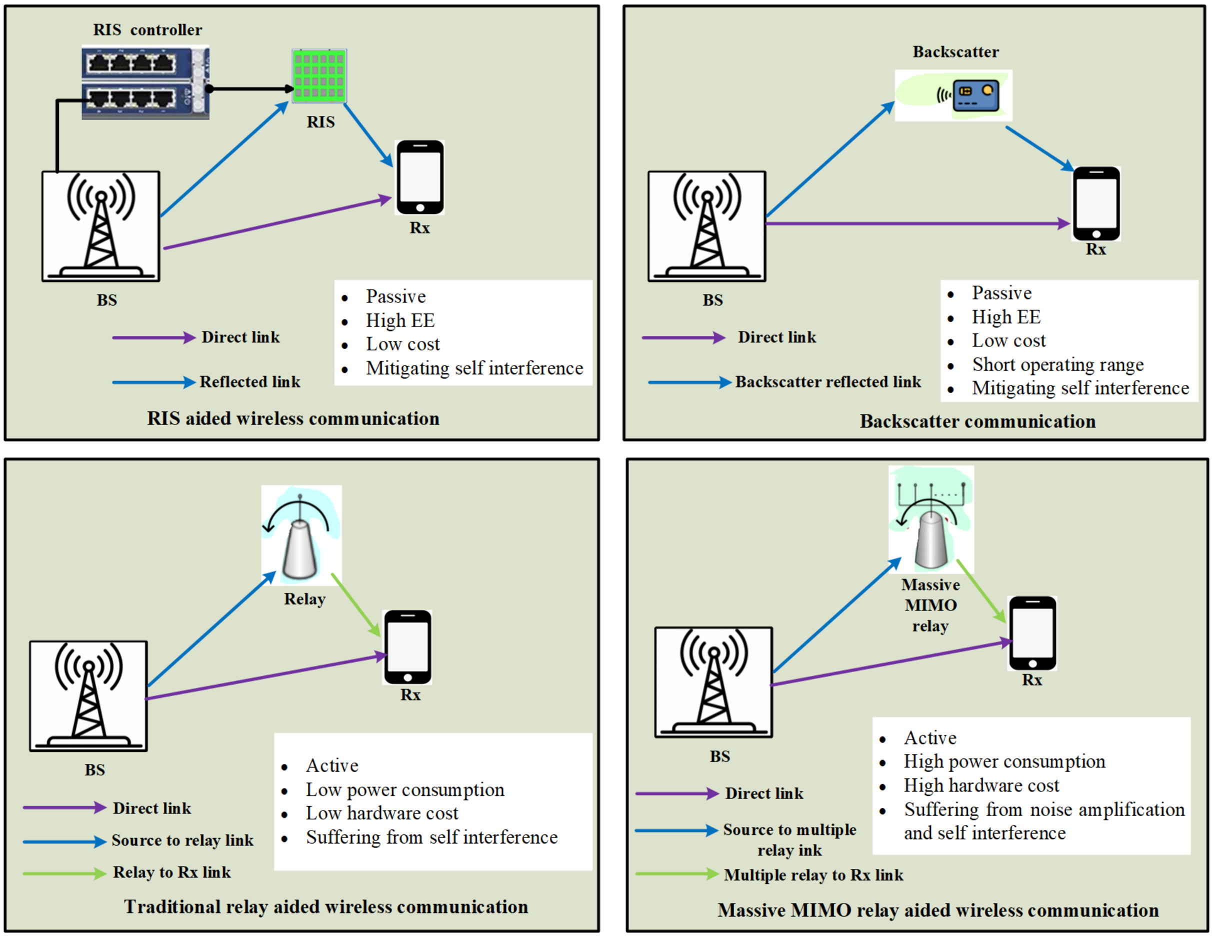

Fig. 5. RIS comparison with current related wireless technologies.

requires communication with the proximal node server only, thus considerably decreasing the network delay. Moreover, ML based intelligent IoT network also aids in saving radio resources essential for data training [12].

III. Design of RIS for IoT Networks

This section discusses RIS operating principle, RIS functionalities, advanced architecture, classification, hardware model, and signal model for wireless communications. Besides, we describe the SDMs operating principle, the architecture of SDMs for IoT networks, applications, and key technical challenges. The large bandwidth requirement in next generation radio networks makes the propagation environment more difficult as smaller amounts of scatters and excessive absorption losses introduce the shortage of rank, channel and vacant links between the user and the Rx. Also the complexities of beam designing for high-bandwidth antenna arrays are not easy to overcome. As demonstrated in Fig. 5, the RIS concept can be viewed to operate similarly to other related wireless technologies, such as backscatter communication, traditional relay and massive MIMO relay enhanced signal transmission and reception. However, the deployment and utilization of RISs can facilitate providing the best propagation conditions by passive signal reflections which creates energy and cost effective transmission atmospheres resulting in enriched system efficiency.

A. Physical and EM compliant models

RIS indicates a two-dimensional (2D) physical object which has programmable macroscopic tangible features and can configure EM wave reaction in a dynamic and goal-oriented way, possibly turning the wireless environment into a service, and for realizing new transceiver designs and network elements at a lower complexity and power consumption. In order to enhance the received signal's robustness at the end points, the channels among the receivers (RXs) and transmitters (TXs) can be governed in RIS-assisted communications that was not possible in traditional cellular communication networks. This section presents the basic theories governing the RIS functionalities and the communication among RIS and EM signals. An investigation of classic RIS functionalities and the relevant protocols is also included here.

1) RIS operating principles: Fig. 6 (A) depicts an RIS-aided communication system that acts as a reflecting surface by consisting of N passive elements. Particularly for the reflection, for the regular surface of the medium, the angle

TABLE IV
EM FUNCTIONALITIES AND THEIR APPLICATIONS OF RIS.

EM functionalities	Action types	Where to apply
Anomalous reflection	Direction	Multi-user wireless communication
Wavefront shaping	Amplitude	WPT
Absorption	Amplitude	Interference mitigation
Frequency shifting	Frequency	Secure data transmission
Nonreciprocity	Frequency and space	FD communication
Focusing	Amplitude	Multi-channel signal transmission

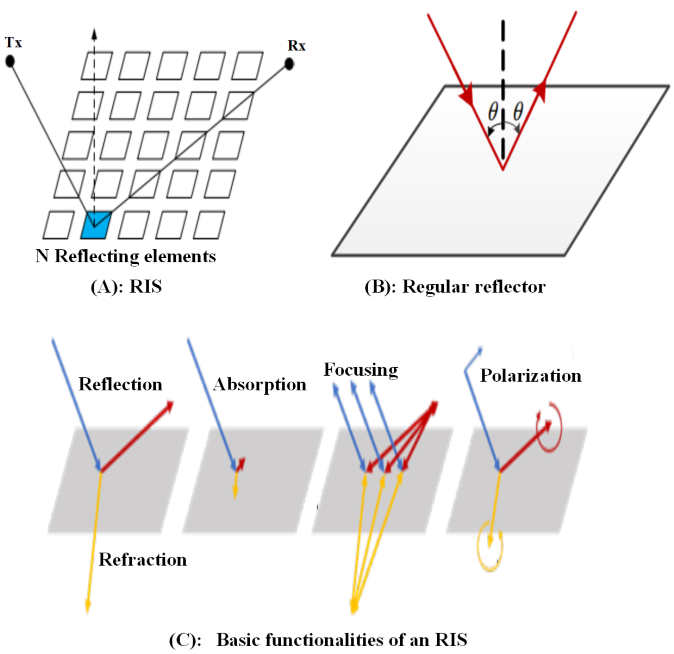

Fig. 6. The working principle of RIS.

of incidence is the same as the angle of reflection as shown in Fig. 6 (B). Every meta-surface autonomously adjusts the reflection angle and the phase of reflected ray, following the comprehensive Snell's law. Besides, for serving an end user in near and far-field areas, patch-array assisted RIS can be shaped where single-beam reflection is considered. An RIS is to use a passive reflectarray whose components' antenna termination can be managed electronically to backscatter and phase-shift the incident signal. The reflectarray-based RIS can be thought of as providing powerful centralized analog beamforming abilities in beneficial positions that can be utilized by communication endpoints. However, to form the reflected beam with incident EM wave, the phase shift of the surface component has to be set properly or smartly, where signal processing design procedures or ML-based methods can be applied, ensuing in the so-called RIS. Each RIS component may consist of manifold constitutive components which are typically referred to as unit cells. The unit cells that construct each single RIS component have, in general, diverse shapes and sizes. If the RIS components are formed of the identical unit cells and if they are organized on a spatially periodic array, the ensuing RIS is a quasi-periodic construction and the inter distance between the RIS components is typically referred to as the period of the metasurfaces. A flat artificial metasurface is comprised of many passive reflecting components with the impinging EM waves that can be intentionally controlled through connected passive components, such as phase shifters, in a way that enhances the performance of wireless systems. They were initially conceived for applications in the optical field to permit economical and strong planar optical elements replacing further luxurious custom-made lenses. Moreover, anomalous reflection and beamforming are more popular than other RIS operating functions and configurations in wireless communications. According to the wave-optics viewpoint, anomalous reflection indicates the conversion of a wavefront from a plane wave to any other plane wave and anomalous beamforming indicates the conversion of a wavefront from a plane wave to a preferred wavefront. The variation of coding matrices pre-stored in the FPGA assembled with RIS assists to reconfigure, adjust, and control the EM wave propagation resulting in numerous EM functionalities such as reflection/refraction, wavefront shaping, focusing, anomalous reflection, absorption, frequency shifting, nonreciprocity, polarization etc., as represented in Fig. 6 (C). Table IV provides several EM functionalities of RIS-enhanced signal transmissions under different communication situations. There are various functions of metasurfaces from which the potential ones are presented below.

- **Reflection/refraction:** Reflection/refraction is reflecting/refracting incident radio waves to a specified direction that does not necessarily coincide with the incident direction.
- **Wavefront shaping:** Metasurfaces have displayed their powerful abilities in manufacturing the EM wavefronts. The digital coding and programmable metasurfaces have benefits of simplifying policy processes and switching diverse functions in actual time, which can be used to shape both signal reflection and transmission wavefronts on a shared aperture [47]. Moreover, the full-space wavefront shaping can be vigorously exchanged between reflection or transmission approaches through varying the positive-intrinsic negative (PIN)-diodes [48].
- **Focusing:** For focusing EM fields, RMSs can be employed. RMSs can create random focusing spots through the utilization of particularly planned coding constraints where the field strength at every spot can be governed autonomously [86]. In addition, for focusing the diffused fields in a highly-efficient and dynamic pattern, a configurable Huygens' metasurface was adopted in [87].
- **Anomalous reflection:** Metasurfaces can interface quick phase shifts through the design of relevant meta-cells resulting in phase breaks. The phase-gradient space-coding structure assists the RMSs in adopting atypical reflection according to the comprehensive Snell's rules

[93].

- **Wave absorption:** The unapproved device's entrance can be blocked through metasurface configuration for ensuring the least or completely no refraction or reflection of incident waves, where a plane wave is considerably abridged in its amplitude. Moreover, wave absorption characteristics can enhance the PLS and stop eavesdropping [89].
- **Frequency shifting:** The RMSs enable the regulation of reflection waves' spectrum in the frequency domain using the time-domain modulation of metasurface characteristics. Furthermore, the transmission of appropriate time modulation signals i.e. harmonic frequency production [28], [95] and frequency transformation [93] on RMSs aid frequency shifting.
- **Nonreciprocity:** Programmable persuading of proper spatiotemporal phase gradients through digital coding modulation introduces the time-changing method and utilizes the space-time-coding RMSs for breaking reciprocity [94]-[95]. Besides, while implementing the backward and forward nonreciprocal communications, the transistor amplifier-aided RMSs do not use the time-changing modulation.
- **Polarization alteration:** The reflection/refraction or focusing operation also involves altering the incoming wave's polarization, for example, linear polarization to circular polarization conversion. Furthermore, reconfigurability requires that the parameters of each function can be dynamically altered, for instance, the direction of reflection/refraction, the focal point location, and so on. A distinct interface can autonomously manage polarization in every direction in real-time, and the EM waves can convey various information that gains the possibility of multiplexing.

2) Advanced RIS architecture: Table V presents the summary of different categories of RIS structures and their advantages and disadvantages as well. Fig. 7 presents a design of RIS that divides the entire metasurface into several parts and implements various architectures in various subsurfaces at a time to increase the next generation network flexibility. For realizing numerous functionalities, there are sparse sensors, active and passive elements, and a dedicated subsurface in this hybrid RIS structure where interference avoidance can be done by turning on the absorption mode instead of transmitting/reflecting signals. Furthermore, this advanced RIS is able to support various working modes as well as gather sensory data from the environment and transmit when needed. Also, with the assistance of an advanced RIS architecture, the UE signal can be improved in both the near-field and far-field cases. For near field applications, the RIS is probable to improve the signal strength for UEs situated at targeted positions in terms of RIS, while decreasing the signal at other positions. For far-field applications, the RIS is usually estimated to increase the signal strength for UEs situated at targeted angles in terms of RIS. We can consider a smart radio environment with RIS where user A is located away from the BS and thus its received signal strength is poor. But user B experiences good signal quality with worse channel conditions. In both situations, RIS can optimize the problems which are shown in Fig. 7.

Several modern functionalities such as interference elimination, channel stability, multipath/ Doppler justification can be achieved using advanced RISs. Fig. 7 shows the overall structure of RIS which not only facilitates the current technology, but also assists the realization of RIS-based PHY slicing in upcoming 6G networks by supporting metasurface sharing with multiple RIS structures. Moreover, this is expected to be easily reconfigurable in order to adjust the area of various types of subsurfaces in real-time networks while enabling PHY security, data transfer, wireless charging and so many other diverse applications concurrently.

3) Different categories of RIS based on structure, energy consumption and tuning mechanism: According to the configurations, patch-array or metamaterial aided tools facilitate the adaptation of RISs. As an instance, microstrip patch antennas on printed-circuit-board material are usually employed. To allow these components to dynamically change the phase over the aperture, the features of resonance of the component must be changed or a variable phase shift must be added per component. This can be achieved by combining traditional probe-fed microstrip patch antenna arrays with anisotropic Huygens metasurfaces. Metasurface denotes the Metamaterial-aided RIS. RISs can be reorganized electrically, thermally, or mechanically following the tuning techniques. Furthermore, taking energy consumption into account, there are three categories of RISs, such as passive-lossless, passive-lossy, or active. However, RIS's passive or active characteristics define their overall efficiency obtainability. But as the RIS can be configured, it is not fully passive. Moreover, three vital RIS functioning actions i.e. waveguide [51], refraction [52], and reflection [53] are discussed in this section. The refracted and reflected EM area is investigated using Love's field equivalence theory [54] which produces equal surface magnetic and electric charges [55]. Using the three functioning actions, the RIS transforms a wave into a desired type of wave and propagates it in the atmosphere.

- **Waveguide RIS:** Authors in [51] investigated waveguide-aided metasurfaces where the metasurface components are designed to be separated by magnetic dipoles and every dipole element's magnitude is relative to the product of each component's polarizability and the corresponding wave. In addition, every metasurface component functions as a micro-antenna and the beamforming of the metasurface antenna needs polarizability tuning. Moreover, the compressed waveguide metasurface is capable of transmitting to wider angles and requires smaller memory capacity than the traditional antenna arrays.
- **Refracting RIS:** Authors in [55] developed a conceptual metasurface model with excellent refraction and reflection abilities using a similar impedance matrix prototype for appropriate optimization of the tangential field elements

TABLE V

SUMMARY OF DIFFERENT CATEGORIES OF RIS STRUCTURES BY CAREFULLY REENGINEERING RIS COMPONENTS [59].

Type of RIS architecture	Advantages	Disadvantages
Passive RIS	Nearly passive and ordinary hardware architecture	Multiplicative PL and less end-to-end (E2E) SNR
Active RIS	Additive PL and high E2E SNR	Complex architecture and high power consumption
Relay-type RIS	Extra coverage and relay-type functionality	Tough modulation and weak incoming radio signals
Tx-type RIS	Cost-effective Tx design, simple modulation and strong incoming radio signals	Large Tx, complex quadrature amplitude modulation (QAM) and low coverage
Reflective-only RIS	Ordinary architecture and single functionality	Restricted 180 degree coverage
Transmissive reflective RIS	Covers every angle and combined functionality	Complicated architecture and functioning approaches
Interconnected RIS	General architecture and little delay	Trustworthy feedback link and non-standalone functionality
Standlone RIS	Individual functionality and dependable design	Complex hardware architecture and base-band radio signal processing

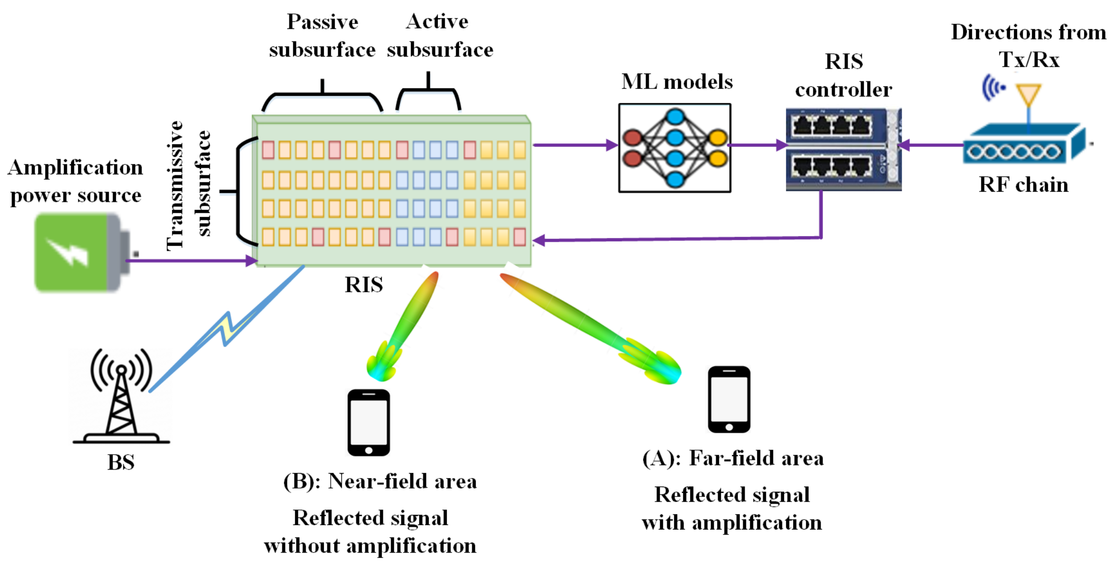

Fig. 7. Advanced RIS architecture [59].

at the metasurface's both sides. Furthermore, three potential device attainments, such as non-native metasurfaces, self-vibrating teleportation metasurfaces and lossless element made metasurfaces are explained in the paper which also mentions the necessity of omega-type bianisotropy while designing perfect refractive surface based lossless-element applications.

- **Reflecting RIS:**The authors in [53] proposed a space-time block coding reflective metasurface where the components in the metasurfaces comprise varactor diodes with a tunable biasing voltage. Through pre-designing numerous digitized biasing voltage levels, every component can use discrete phase shifts and attain beamforming for the reflected wave.

4) Hardware model: In general, there are two parts of RIS hardware designing, such as an intelligent controller which makes decision autonomously and the multiple layered planner surface [6]. Fig. 8 shows a typical three layer design where

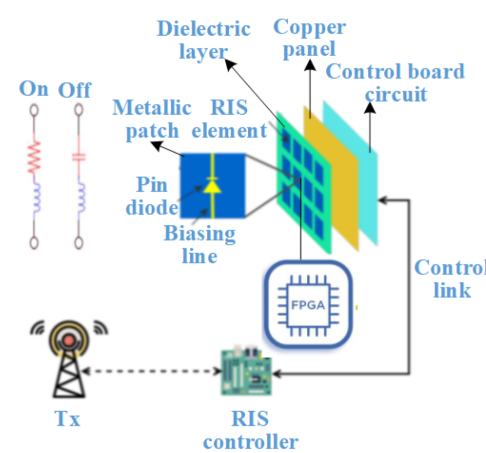

Fig. 8. Hardware model of RIS [61].

the lot of printed elements made up of dielectric substrates in the external layer are capable of interacting with the incident waves directly. Besides, the copper panel based middle layer can prevent all types of signal emanation and the controlling circuit board in internal layer can adjust RIS phase-shifts. Moreover, the intelligent controller, such as a FPGA is responsible for reconfiguring the RIS components that communicate with the BS which also acts as a gateway in the IoT network. The reconfigurability of the RIS is ensured by a network of tuning circuits and a biasing line that controls the unit cells. Depending on the control voltage applied throughout the biasing line, the scattering properties of the RIS are adapted to the channel and network conditions, making it digitally controllable. The state change of PIN diode is done through limiting voltage using biasing line for adjusting the RIS phase-shifts. Moreover, the PIN diode can be transferred between on and off conditions to realize the phase-alteration of π in radians. In addition, for enabling the sensing abilities while approximating wireless channels, cost effective dedicated sensors can be added with the RIS components in the IoT network.

5) Signal model: This section discusses how to incorporate the existence of an RIS of a channel model in the propagation environment as they are crucial in theoretical investigations and simulations on RIS-aided systems. Accurate channel models can compare with other techniques i.e. relaying, thus turning vital for the evaluation of RIS. Suitable designing method selection depends on the RIS implementation process that may be metasurfaces or reflectarrays [59-65]. By grasping the Huygens standard, the RIS power distribution is generally expressed as an integral that reports the effects of the total surface in a wireless environment which does not consider reflection, shadowing and scattering [66]. Besides, obtaining the closed-form integral expressions is complex, except for several asymptotic regimes, which correspond to viewing the RIS as electrically trivial and electrically bulky in terms of the signal transmission distances and wavelength. Moreover, components of a conventional precoder can take any worth satiating certain constraints, e.g. power, although the additive term in RIS effective channel lies on the radio propagation environment and is only partially manageable through the RIS. However, this makes the RIS optimization task further challenging. The network planner gets additional dominance on operative channels because of stronger additive RIS impact compared to the combining and controlling impacts of the traditional multiplicative precoders [67]. Two RIS channel designing methods are presented below:

Electrically small RIS: This asymptotic governance considers the RIS as a compact-shaped spreader according to circulation distances. Generally, the PL balances with the reciprocal of the multiplication result of the distances among Tx-RIS center and RIS center- Rx. Additionally, RIS size increment increases the received power that is generally done using anomalous reflection method, where the RIS created PL maintains the “product of distances” approaches, which

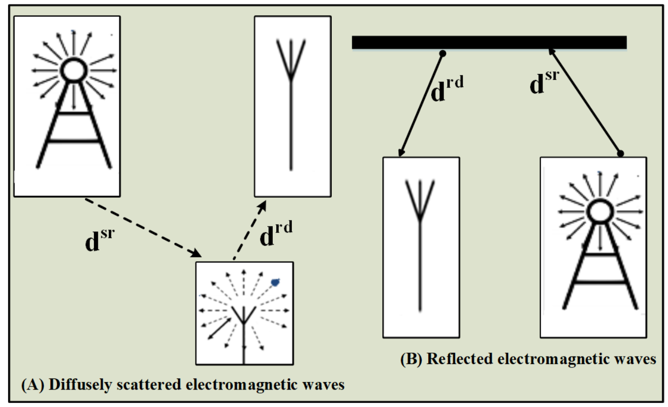

Fig. 9. Large-scale PL [4].

is expressed as [13]:

$$L(d^{sr}, d^{rd}) \approx \lambda_s (d^{sr} d^{rd})^{-1}, \quad (1)$$

where λ_s means the coefficient of the electrically small scenario, d^{sr} and d^{rd} symbolize the distance of Tx-RIS and RIS-Rx links, respectively (more detailed explanation in [58]). **Large scale PL:** Reducing the vast amount of transmission PL using RIS is a vital necessity during channel planning but due to the efficiency evaluation limitations, it is more difficult than other techniques [69] which is a distinguishing feature among metasurface and reflect array aided RIS. Considering reflectarray-assisted application, Fig. 9 shows the impacts of one RIS element where every component works as a regular antenna with a $\lambda/2$ ordered dimension. On the other hand, every component in a metasurface-aided RIS acts as a metasurface tile with magnitude ordered dimension that is bigger compared to the wavelength. It is worth mentioning that tangible size has a substantial impact on the interaction method among objects and instant EM waves [70]. Usually flat barriers such as walls, buildings etc., which are quite bigger compared to the wavelength, the barriers which have similar dimensions to the wavelength, extensively throw the incident wave in all angles. As per long term observation from field measurements [71] as well as site-specified ray-tracing simulations, it provides more reliable outcomes [72]. Moreover, at millimeter-wave frequencies, the magnitude of objects that can act as reflectors turn into minor.

The components of the reflectarray-based RIS work as an extensive thrower that sprinkles the received point from the incident wavefront to every angle surrounding the component causing more energy waste on the way to the Rx device. The UE location in the stochastic simulation is shown in Fig. 10 where there are single transmitting antenna-based UE, 16×16 passive reflecting components equipped RIS and 4×2 uniform planar array (UPA) antenna panels attached a BS. Though RIS is positioned at 2m height on the YZ plane, BS is located at 3m height on the XZ plane and has 12m and 15m distances from the Z and X origins respectively. Moreover, there are 8m distances among the UE antennas and they are positioned at 5m height. Besides, the UE is placed at the nearest position

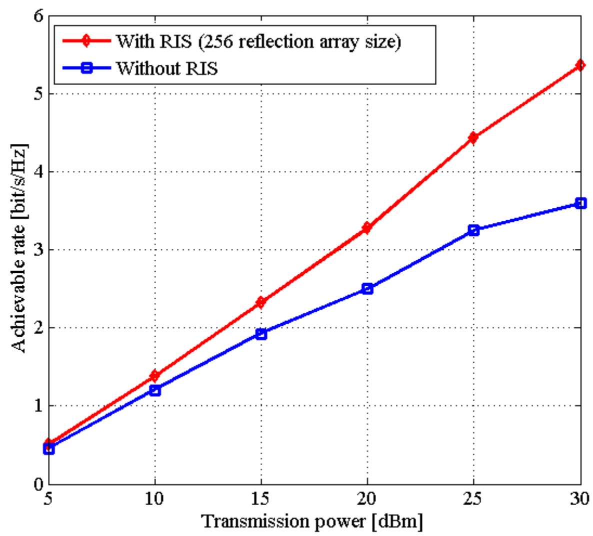

Fig. 10. Comparison of variation of achievable rate with transmission power.

from the RIS which is constant 1m. This figure considers the Rician fading model. The channel matrix is given by

$$h = \frac{1}{\sqrt{z+1}} h_{NLoS} + \sqrt{\frac{1}{z}} h_{LoS}, \tag{2}$$

where z, h_{LoS}, and h_{NLoS} represent the Rician factor, deterministic LoS component and independent and identically distributed Rayleigh fading coefficients. Let, z_r, z_v, and z_d be the Rician factors for RIS-BS, UE-RIS and RIS-UE links, respectively. We use $z_r = \infty$ which corresponds to a pure LoS channel, $z_v = 1$, and $z_d = 0$, which corresponds to a NLoS channel. We change the transmission power to observe the attainable data rate for 16×16 reconfigurable array sizes. The achievable rate is compared for reflecting array sizes of 16 × 16 and without RIS while changing the transmit power is shown in Fig. 10. The 16 × 16 reflecting array with full CSI provides better system performance than without RIS. Therefore, the point of reflection utilizes large reflecting arrays which reduces the energy wastage for channel estimation. Besides, every component in a big enough metasurface-aided RIS works as a reflector that reflects a received segment from the incident wavefront based on a controllable reflection angle. In addition, no additional scattering of the wavefront takes place in metasurface tile where Snell's law is not followed by the angle of reflection and this type of reflection is generally termed as anomalous reflection [73]. Fig. 9 (B) describes the large PL of reflected EM waves. Therefore, the PL over the RIS component will be related to the entire distance considering the metasurfaces-based RIS [75], $d = d^{sr} + d^{rd}$, i.e.,

$$PL^{reflected} \alpha \frac{1}{d^n}, \tag{3}$$

where $PL^{reflected}$ denotes the large scale PL of reflected EM waves and n stands for the PL exponent, which is equal to 2 in the air. Fig. 9 (A) describes the large PL of diffusely scatter EM waves. The PL will be proportional to the product of the distances for reflectarray-assisted RIS [71-75], $d_p = d^{sr} \times d^{rd}$, such as

$$PL^{scattered} \alpha \frac{1}{d_p^n}, \tag{4}$$

where $PL^{scattered}$ denotes the large scale PL of diffusely scattered EM waves. PL scaling using RIS has become a controversy topic in modern studies [75], particularly the hypothesis, which states that a metasurface works almost as a specular reflector that is only legal in particular situations associated with tangible RIS size and distances of RIS-Tx and RIS-Rx links. There are some key open research scopes in RIS-integrated IoT systems, in spite of the earlier research investigations on the efficiency estimation. Those crucial research topics are explained below:

- **PL experiments for outdoor scenarios:** With the existence of scattering and reflecting items in free-space atmospheres, the expansion of theoretically-authenticated PL models has been a prominent research scope according to the experimental PL measurement issue mentioned in [74]. While estimating the realism of RIS-enabled communication systems, PL can be a vital limitation because of using RIS as it only supports co-phasing gains and is a passive device. Backscatter channels and clear relaying undergo serious PL as a result of extra signal transmission at the backscatter tag or relay node. Conventionally, smooth surfaces considerably greater than the wavelength are modeled as reflectors [69], [71], which provides metasurface-based RIS an enormous benefit over reflectarray-based RIS. Though, this is still essential to be validated experimentally. Measurements for 0.35λ-spaced reflectarray-based RIS were described in [74]; but, it is stagnant not clear whether the tighter packing of scatterers in a metasurface-based RIS would increase on these outcomes, particularly for those who have the same gross physical mass. However, those issues can be resolved using the ML-enabled PL calculation.
- **Exact distributions:** Currently, the efficiency exploration methods work according to the approximated distribution and central-limit-theorem (CLT)-aided distribution approaches [75-77] but they provide correct outcomes in greater signal-to-noise-ratio (SNR) [78] systems only. Consequently, in order to analyze the system efficiency and diversity order [79] in a small-SNR system, further developed perfect systematic models are required.
- **Hardware limitations:** A number of hardware constraints, such as the number of quantization levels of the RIS phase shifts show extreme impact on the attainable system efficiency in real-time environments. The sprinkling environment is possible to fully cover using an RIS but the highest amount of integrated components and the

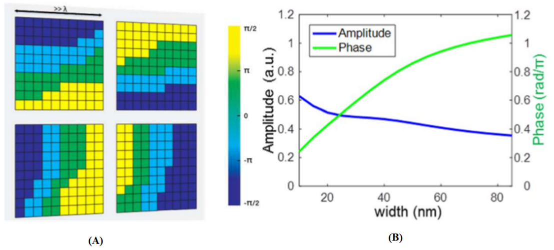

Fig. 11. Design of transmission mode metasurfaces [4], [82].

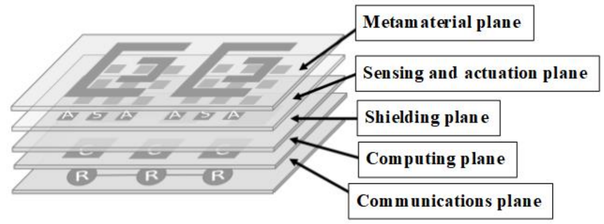

Fig. 12. Diagram of the general structure of an SDMs which denotes actuators-A, sensors-S, controllers-C and routers-R [83].

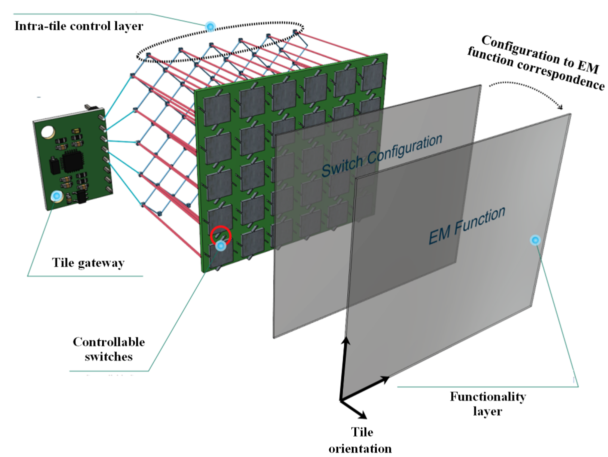

Fig. 13. Architecture of SDMs for IoT networks [25].

large amount of RIS phase shift's quantization stages are such limitations [79-81].

B. Programmable metasurfaces

Metasurface can significantly facilitate the real-time RIS implementation [14], [82-83]. In general, metasurfaces are electrically thin having reduced thickness but big transverse size than wavelength. Moreover, they are homogenizable as the spaces among nearby unit cells are lesser than the wavelength and have a sub-wavelength composition because of having shorter size of unit cells compared to the wavelength [5]. As shown in Fig. 11 (A), the simplest way to implement an RIS is to use a passive reflectarray. The metasurface building, including meta-atoms as its structure block, is a sophisticated metallic or dielectric small scattering particle that is periodically frequent over an assured area to generate a planar which is also called a tile. There are a number of tiles in the metasurface of an RIS in which every tile works as a separate surface and defines the boundary of a reflectarray due to the reduction of antenna spacing and antenna size as well as the almost continuous amplitude/phase profile applied through the surface. These sub-surfaces provide significant flexibility to manipulate incident wave-fronts while smoothly controlling the scattered electric field as well. For instance, the tiles are capable of reflecting the incident waves towards various directions. Besides, the changes of the amplitude and phase of a signal transmitted via metasurfaces with respect to silicon nanobeams are shown in Fig. 11 (B) where the nanobeam's phase pickup range is lower than 2π. However, if nanobeams having multiple widths are organized at deep sub-wavelength spacing becomes lesser compared to the wavelength, a titled phase wavefront having a big phase gradient can be generated.

1) Related works: The present investigations mark the metasurface and reflectarray as promising techniques for making configurable metamaterials [12], [14], [50] which makes them utilizable in RIS-based next generation IoT networks. Also, the system model and associated functionalities have been analyzed in some relevant studies. Table VI provides a summary of the SDMs related recent research works.

2) General structure of SDMs: SDM mechanisms usually adopt configurable capacitors or resistors that update their value according to the directions of the controller and thus the SDM actions are determined. SDM contains a graphene sheet which is intrinsically configured and the SDM controllers manage the variation of electrostatic bias in various parts of it. Apart from the tangible features, Fig. 12 presents the basic logical organization of SDM which is discussed below:

Metamaterial plane: The expected EM features are realized by the metamaterial plane using a reconfigurable pattern where complementary metal oxide semiconductor (CMOS) switches or graphene substances are adjusted through the variation of electrostatic bias [83].

Sensing and actuation plane: Low power devices/sensors have been integrated in recent metasurfaces for avoiding peripheral controllers by determining the change of phases internally resulting in more flexible and automatic functionality of the metamaterial plane.

Shielding plane: In order to eliminate interference, the shielding plane separates the upper and lower plane's functionality where the use of a normal metallic layer in the metamaterial plane at this end can assist in reflecting EM waves.

Computing plane: For changing the metamaterial plane's EM status effectively, the computing plane performs external instructions received through the interface and inner instructions got from other sensors or controllers where a single controller is able to direct multiple actuator functionalities.

Communications plane: Through virtual or wired connection, the communications plane organizes the computing plane functionalities and communicates with exterior components using the SDM interface.

TABLE VI
SUMMARY ON EXISTING RESEARCH IN SDMS.

Title of Surface	Ref.	Year of publication	Metamaterial plane	Computing functionality	Sensing and actuation functionalities	Communications between layers
SDMs	[28]	2016	Unit cell with a metal ground flat and a rectangular patch surface	FPGA-assisted control board linked to deputize-metasurfaces	Actuation empowered via a control voltage utilized on the PIN diodes	Wired link through control board, computer, and metasurfaces
RIS	[82]	2018	Reflectarray antennas	No computation in passive reflectarrays	Controller- assisted sensing and reflecting manners	Regulator to passive reflectarrays
VisorSurf HSF	[83]	2017	Graphene and CMOS switches	Huge cores, inferential computing and infinitesimal computation procedures	Sensors included into SDMs	Network on chip and nano networking
Smart Reflectarray	[84]	2016	Reflectarray antennas	No computation in passive reflectarrays	Reflector arrays are regulated by a bias voltage to adjust the varactors	Regulator to passive reflectarrays
Digital coding SDMs	[85]	2018	Space-time block coding metasurfaces with components linked by biasing lines	Frequency-based amplitude and phase modification	Actuation obtained by a control voltage loaded to PIN diodes	Wired link among SDMs and FPGA

3) SDMs for IoT networks: Aiming to build an IoT intelligent network, additional potentials of modifiable metasurfaces such as sensing impinging EM waves, such as wave focusing, absorption, imaging, scattering, and polarization as well as inter-controller communication and data processing etc. can be realized through deploying highly capable controllers instead of actuators of the cells. Consequently, when cured macroscopically, the permittivity and permeability of metamaterials are entirely defined through the meta-atom construction and can be modified locally into any configuration of select to shape impinging EM waves, removing the essential to create new radio signals and decreasing whole network power consumption. There is a gateway to interact with the outer world maintaining typical communication protocols and thus this network is accessible to computer software in order to enable easy and effective reprogramming and controlling of metasurfaces. However, interconnected metasurface networks are generated as the computer software can interface numerous metasurfaces where the adaptation of IoT devices can unlock extra functionalities as shown in Fig. 13.

In a network with massively deployed functional metasurfaces, the controller-gateway instruction interchanges enable fault avoidance of metasurfaces because faulty actuators can be avoided by routing data again or the desired controller can be reached in spite of facing several links failures [68]. Moreover, for achieving the required functionalities, the actuator states can be configured by impinging wave determination, thus exploring the proficiencies of finding distributed sensory measurements. Only lately have SDMs been deliberated for terrestrial cellular communication applications according to progresses in tunable changing elements that are built-in the meta-atoms and obtain guidelines from an exterior programming interface comprising of software defined functions that modify the meta-atom building vigorously and, thus, reconfigure and utilize the strictures of incident and reflected waves' such as phase, amplitude, frequency, and polarization, to empower the EM behavior of interest [14].

Based on the expected functioning bandwidth, actuator's real-time operational procedures, controller abilities and their interconnection, there may be variation in SDM deployment where wired and wireless controller networks enable asynchronous and synchronous communications respectively. There is a multiple layer based printed circuit board in the metasurface that can reflect signals with the cooperation of the controller, transceiver and antenna. In order to enable configurable functionalities in intra-metasurface communications, the theories of computer science and communications are exploited while utilizing SDMs. A swift of the hardware building proposed in open literature to realize crucial operational principles of SDMs, was provided in [14]. Moreover, the integrated software performs the software defined features maintaining the common network protocols for facilitating easier operations of the metasurfaces. Certain metasurface functionalities comprise beam steering, beam splitting, wave absorption, wave polarization, and phase control. Authors are mentioned to [25] for a full outline of SDM antenna construct principles and EM employed topologies.

4) AI empowered metasurfaces: For realizing the preferred EM function and supporting dynamic utilization of SDM characteristics, an SDM combines metamaterial system and network controller together [25], [86]. In addition, the activation or deactivation of the controllers-connected switches assists in determining several metasurface features, such as impedance, bias, or patterns. Moreover, reusable software modules can integrate proficient learning techniques and thus realize numerous SDM characteristics simultaneously and dynamically. However, a complicated SDM organization is required for maintaining the expected overall performance by assuring extensibility, overhead and energy depletion. Considering this situation, ML methods are considered auspicious while empowering intelligence in SDM systems where the amount of attached controllers and sensors may rise fast [42]. However,

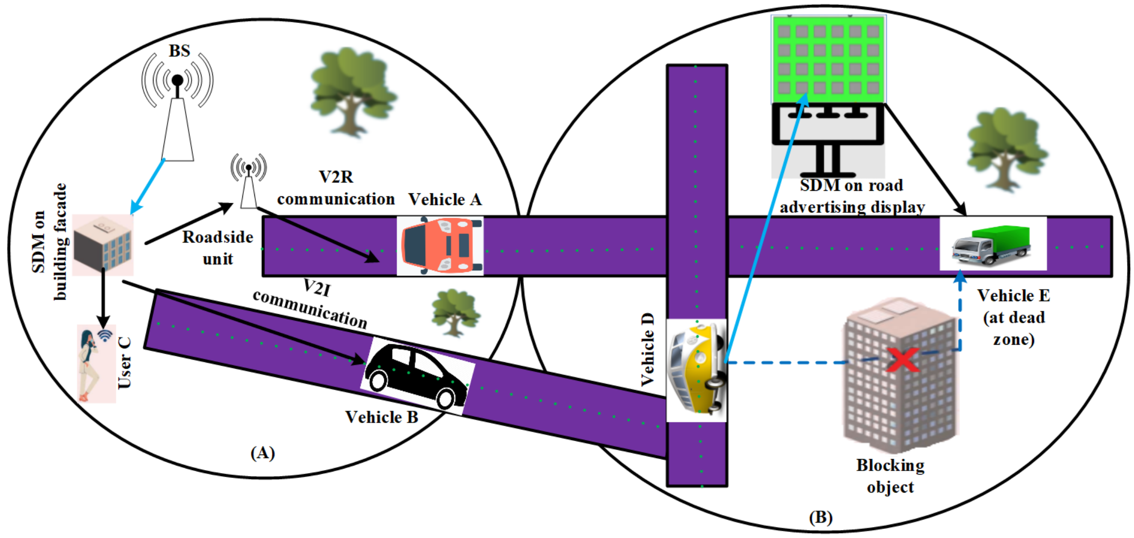

Fig. 14. Typical SDM applications envisioned for IoT networks [14], [24].

comprehensive investigations of ML-based SDM-assisted IoT networks can be a promising research scope. Moreover, ML techniques provide sophisticated real-time resolutions in response to the common concerns of wireless networks which includes detection, estimation, optimization, and classification. Additionally along with the SDM's potentiality exposing, newly arisen problems should be explored also for its effective utilization. We focus on several crucial ML employers and the related issues while looking at SDM-based systems. According to the existing studies, there are three major types of learning methods, such as SL, USL, and RL. Besides, DL is a particular branch of ML methods which is mainly a hybrid procedure as it is able to incorporate various methods from the three types of ML techniques to inherit their robustness as well as minimize their limitations.

5) Applications: This subsection presents various distinctive application scopes of SDMs within smart wireless situations.

Multiuser communications: For supporting a number of users via beamforming/beam steering and beam splitting, the metasurfaces can assist in muiltuser downlink transmission which is shown in Fig. 14 (A) [24].

Metasurfaces as relays: Operating the metasurfaces as reflective relays is an impressive usage for enhancing the quality of service (QoS) of users experiencing dangerous transmission surroundings as presented in Fig. 14, which illustrates the realization of relay functions using metasurfaces reducing the hardware complexity which is shown in Fig. 14 (B) [14].

Stationary scenarios: Appropriate SDM configuration can control the NLoS signals in poorly covered zones, in which shadowing/obstructions don't let the LoS communications happen. Also the redirection of several unwanted signals can be done through SDM configuration for avoiding interferences with more simultaneous transmissions, or generating damaging interferences in the direction of harmful UEs. Moreover, SDM installation can facilitate the self-directed fixed low-powered IoT devices with maintainable recharging through transferring energy. Similarly, deployment of SDM can assist numerous fixed setting based potential applications to increase the efficiency of IoT Networks.

Mobility scenarios: The movement of UEs within SDM aided IoT networks is usually managed by UAVs, where tracking abilities are utilized by passive beamforming of fixed positioned RISs. Besides, the RISs' movement is also noticeable where SDMs are integrated with a UAV so that they merge the degrees of freedom of the UAV as well as the SDMs [87]. Large possibilities of LoS connectivity is a very promising feature in SDM-aided mobile infrastructure but the relevant system architecture may be highly complicated. Furthermore, the stable re-organization of communications and channel approximations can be advantageous from the spatial variety and higher quality of signal.

RIS assisted massive MIMO communication: Massive MIMO is a potential technique to enable a vast improvement of both the SE and transmission gain but its real-time deployment is tough due to over infrastructure price and huge energy consumption issues. However, these problems can be solved by integrating RIS in massive MIMO systems while providing optimal performance gains as illustrated in Fig. 15 (A). Hence, for achieving the highest efficiency in RIS-enabled massive MIMO networks, efficient resource allocation, delay reduction and beamforming designing strategies require further investigation.

RIS assisted FD transmission: Fig. 15 shows RIS-assisted FD transmissions where the reprogrammable FPGA enables each RIS component distinctly to reflect incident waves autonomously.

i) LoS scheme: An RIS-based LoS communication network is illustrated in Fig. 15 (B) where FD communication happens among Tx and Rx by transmitting several copies of same data

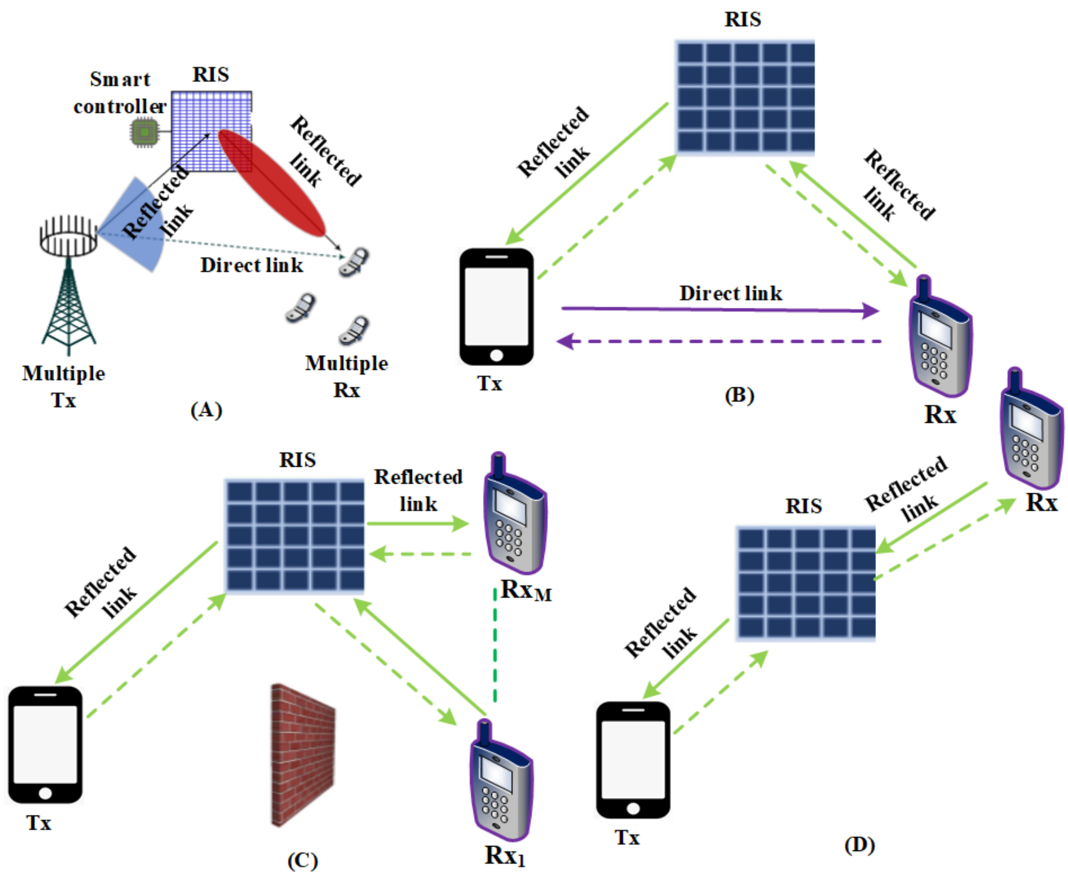

Fig. 15. Envisioned RIS-enabled IoT applications in indoor and outdoor scenarios.

using reflective and direct links to achieve diversity gains as well as greater received signal-to-noise ratio (SNR). Here, RIS can utilize its asymmetric/symmetric characteristic because the source position may be asymmetric.
ii) NLoS scheme with reflect waves: In Fig. 15 (C), the FD data transmission from single source to several destinations in NLoS environment completely relies on the reflection of RIS where the sender is not informed of the Rx location. In this scheme, more enhancements of RIS components' reflect matrix can significantly facilitate realizing FD communication in blind zones.
iii) NLoS scheme with transmission waves: In an NLoS environment as displayed in Fig. 15 (D), the Tx and Rx devices are placed in the opposite sides of the RIS that does not permit LoS communication, however, RIS facilitates performing FD transmission as like LoS environments.

6) Key technical challenges: Though the metasurface provides numerous facilities, there are some problems also which require tracing in order to enable the complete strength of 6G networks. The challenges are explained below:
Dynamic structure design: In order to realize a number of characteristics within real-time wireless networks through the proficient RMSs function, the configuration ability of a meta-atom comprises a crucial designing issue. On the other hand, various existing investigations explained numerous achievable characteristics of metasurfaces but achieving numerous characteristics like nonreciprocity and learnability at a time seems to be rare [25], [28]. Therefore, by controlling every single metasurface cell individually, the development necessity of efficient separated meta-atom controlling techniques will rise which will provide ways to evaluate the efficiency of various metasurface functions simultaneously. In addition, as metasurfaces are expected for installation in extensive frequency band based applications, thus planning proficient metasurface configurations with dynamic frequency shifting capability is a promising research scope.
High-order modulation: In order to enable high-speed transmissions in metasurface-aided wireless communication networks, the modeling of high-order modulation and novel waveform can offer optimistic realizations. It is considered very essential because the present metasurface-aided senders can use only single-carrier low-order modulation patterns, i.e. quadrature/binary phase-shift-keying [25], [35].
Efficient programmable interface: Apart from the necessity to improve SDMs constructions proficient of realizing diverse purposes in actual time, there is a compelling necessity to inspect advanced multi-functional SDMs that can shift from single EM behavior to alternative in a fast method to cater for

the gradually various user loads, especially in giant mobility situations where the system convergence rate may not be within the coherence time of the surrounding radio propagation environment. Consequently, investigation efforts should be focused towards emerging control space-time block coding software that integrates low-complexity and fast configuration optimizers to facilitate the optimization and adaptation of SDMs functionalities to the surrounding radio environment. Besides, advanced signal processing and ML algorithms may be developed to leverage the sensing abilities of digital coding metasurfaces for enabling intelligent wireless network performance optimization, which can converge within the coherence time of the smart radio environment and can be aligned with the 6G network necessities for IoT networks, such as ultra-low latency, massive connectivity, and great dependability [28].

Storage and EE: As SDMs basically focus to sense, compute and process data for enabling intelligent wireless systems, the overhead feedback and sensed data volume are needed for the optimization of the metasurface configuration where EM responses are extremely heavy. Consequently, the requirement of more resources grows according to the storage, computational time, bandwidth and energy.

Computation: As per prediction, the next generation wireless networks will be disparate which will include various enlightened techniques as well as support various necessities providing superior QoS. For coordinating different processes and enabling continuous connectivity by efficient and dynamic adaptation of numerous network parameters, i.e. symbol modulation, frequency band, route selection, coding rate etc., the SDM parameter development may be done which requires investigation on innovative computation processes.

IV. ML for RIS-based IoT Networks

For identifying the finest functioning strategy using data driven methods, different AI frameworks can play an essential role in the field of SDMs. Particularly, ML is the most promising framework among them, which is expected to be vastly utilized in various types of SDMs systems [14]. It applies the ability of dynamic model alteration for processing information using learnable algorithms which are also capable of completing complicated jobs proficiently.

A. Motivation of integrating ML in IoT networks using RIS

This subsection represents the limitations of traditional intelligent IoT systems, the importance of ML integration for overcoming those issues and the system model of ML-enabled intelligent IoT applications. For effective exploitation of RISs in virtual network optimization, the existing investigations in [13-14] identified numerous difficulties regarding link designing/approximation, spectrum distribution and combined transmission and passive beamforming modelling which can be resolved by adopting various efficient optimization methods, such as alternating optimization (AO) algorithm [7], gradient descent approach [88], iterative algorithm [89] and convex optimization [90]. In spite of gaining some significant perceptions, there are still several issues in traditional intelligent IoT systems which are discussed below:

- Most of the studies consider stationary UEs and overlooks their mobility. Moreover, the fully-familiar network atmosphere should be treated as a major issue because the diverse user requirements have not been taken into account.
- The breakthrough of cutting-edge technology and broad coverage of cellular networks in long term evolution advanced (LTE-A) networks constitute an ideal platform for ubiquitous M2M service provisioning on a large scale. However, under the traditional approach, the massive M2M devices always select the evolved Node B (eNB) with the best signal quality for the connection, thereby causing network congestion and overload. Though RIS/eNB cannot learn from any new atmosphere or inadequate user response, the randomly changeable network constraints in real-world intelligent IoT systems steer towards the derivation of perspicacious dual probability allocations considering the tele-traffic requirement and movement of users. In addition, applying traditional optimization processes is really tough due to this extremely varying stochastic atmosphere. Furthermore, the typical spectrum-requirement and inadequate user feedback prolong the limitations of realizing the traditional intelligent IoT systems.
- As per expectation, eNBs will be able to receive the immediate channel CSI but the passive RIS characteristic makes the CSI acquisition highly difficult compared to the traditional relay based networks resulting in more limitations of typical intelligent IoT systems.

B. ML techniques

As a result of having great learning abilities, ML is considered highly effective in revolutionizing communication networks due to its different applications in intelligent IoT systems. An ML-aided technique has been presented in this segment for learning native transmission atmospheres within an intelligent IoT system as well as for predicting the ideal configuration of RIS. RIS not only maintains its typical functionalities but also provides scalability as well as reduces overhead and energy consumption if it can be coordinated properly. Considering the rapid growth of embedded controllers and sensors, ML frameworks are capable of realizing intelligent RIS [13]. According to [14], managing network resources is highly challenging due to the network demands, channel requirements, bandwidth shortage, high power consumption, and memory limitations. Authors in [91] explored various ML algorithms for solving classification, optimization, estimation, and detection related problems in wireless systems. Authors in [41], [43] designed an ML-assisted technique for straight prediction of attainable data-rate at a specific position through utilizing the beamforming vector of RIS reflection with the assistance of its position features along with the anticipated input, however, ignoring the channel estimation error. This paper focuses on key learning techniques as well as traditional

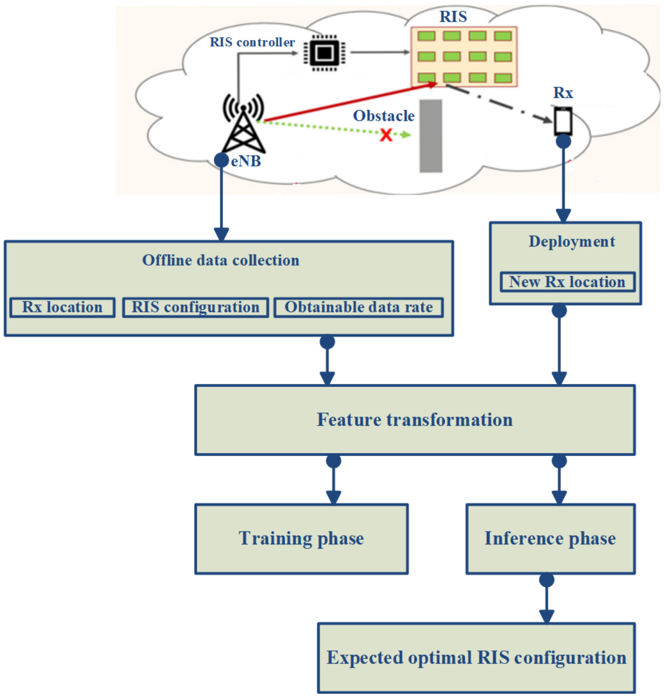

Fig. 16. Proposed framework for the model learning and inference phases [8].

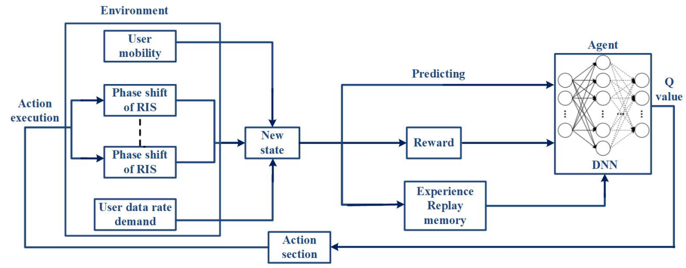

Fig. 17. DRL model for RIS networks.

ML algorithms mentioning both their promises and limitations considering an RIS-enabled environment. Furthermore, the application of ML in RIS-enabled wireless systems facilitates optimizing and controlling the reconfigurable components and also the panels. However, there are still a number of real-time problems in ML- and RIS-enabled systems, such as training distributed models, transfers, updates and so on which should be solved to achieve desired performance.

1) Classical DL techniques: DL-aided technique can learn complicated non-linear interaction based mapping functions by which the optimum configuration of RIS is attained for every Rx position using the estimation outcomes of the model and later the trained model is installed at the controller in the form of a software module. According to the illustration in Fig. 16, this type of framework operates in two stages, such as the model offline training stage and the model inference stage, they are happening in parallel which work with training positions and unknown positions respectively [8].

- **Model training stage:** This stage includes the offline collection of position estimation information from a group of experimental Rx positions, a group of RIS phase-shift settings while communicating among experimental positions, and the equivalent attainable data-rates (as in Fig. 16). Enough capable RIS controller or any distinct calculating tool with relevant data accessibility can perform the offline data gathering and model training processes. For performing the next stage, the DL based model is uploaded to the RIS controller after training.
- **Model inference stage:** At the beginning of the model inference stage, the system takes approximated position data from the anticipated Rx and then determines its distance from every RIS component for forming input. After that, the system constructs input samples for location is created by the use of every potential beamforming vector of RIS reflection according to the pre-prescribed codebook. It is worth mentioning that, the RIS controller is able to perform the inference process, obtain required input information, such as features of Rx position and accessible beamforming vectors of RIS, build the system structure and finally determine the optimum RIS settings according to the model estimated results. However, information exchange causes huge postponement of time in this stage resulting in a significant limitation that requires more research attention to design E2E applications.

DRL techniques: In order to authorize agent-atmosphere interaction, DRL is thought to be a potential AI framework which can mitigate the limitations of traditional intelligent communication systems through learning from atmosphere, user feedback, and mistakes which lead to the efficiency enhancement [15], [17], [92]. Especially, DRL models enable the agents, such as eNB, RIS to behave optimally during agent-atmosphere interaction. Rather than concentrating on present situations only, DRL models aim to improve the system development resulting in substantial advantages which makes them appropriate to tackle various issues of intelligent IoT networks [93]-[94]. Authors in [95]-[96] proposed a DRL-aided framework for mutual planning of the RIS installation strategy and phase shift strategy that takes the users' dynamic information requirement into account. Fig. 17 presents a DRL-enabled architecture where the eNB functions as an agent and with the aid of the installed controller, it manages the spectrum distribution process to UEs, regulates the location and phase shifts of RISs and notices the network condition frequently. Here, state space indicates information regarding a number of issues, such as RIS-user coordination, power allocation to UEs and phase shift of RISs. In order to select the best controlling procedure, eNB performs several actions which consist of the change of location, RIS phase shifts, and assigned power. However, obtaining the highest Q-value constantly in the DQN model by performing proper actions is the main goal of the decision procedure. Depending on every action, the formulated objective function decides a reward/penalty for the eNB.

1) *State:* There are four parts of the state space, such as the present phase shift of every reflecting component of

RIS, present 3D location of RIS, present 2D location of every UE and present power assigned to every UE from the eNB.
2) *Action:* There are three parts of the action space, such as the changeable phase shift amount of reflecting component, movement angle and distance of RIS, and adjustable amount of transmission power of UE.
3) *Reward:* The system EE decides the reward function. If any eNB action increases EE, it gains reward but whenever any action reduces EE, the eNB obtains a penalty.

Challenges of DRL techniques: Because of a familiar misusage, DRL procedures experience an over-estimation on action value that makes them inappropriate to high complexity based SDM network characteristics.

Classical ML techniques: The existing wireless networks utilize various SL and USL based frameworks which are considered to be promising solutions to deal with the issues of intelligent IoT networks as well.

SL techniques: SL algorithms are trained using labeled data. SL algorithms can work in different network conditions to overcome a number of limitations e.g. networking interconnection [97], antenna/channel picking [98], QoE/traffic estimation [99], and resource identification [100]. As a result of having benefits i.e. rapid convergence rate and small complexity, the adaptation of SL algorithms in intelligent radio networks is of superior significance in order to solve various associated difficulties using enough trained information. However, SL techniques lie on previous information which creates them data-hungry.

USL techniques: USL procedures are opposite to the SL techniques due to their zero dependency on previous information which does not make them data-hungry. Therefore, RIS-enabled wireless systems can adopt numerous USL procedures [101] to solve a range of issues including interference mitigation [102], data aggregation [103], network/channel condition identification [104], [105], user association/clustering [101], and eNB installation. Also, USL techniques used for classification of devices are based on attributes or parameters and data compression as well as dimensionality reduction, respectively apart from SL and RL techniques.

Challenges of classical ML techniques: In spite of providing better performance in present network scenarios, typical ML frameworks e.g. SL and USL techniques have become inapproiate for RIS because of different issues, such as (i) dependence on huge volume of data obtainability for achieving poor simplification error; (ii) incapability of meeting the strict necessities of extreme-low latency and low-overhead communications because of huge processing time; (iii) deficiency of closed loop optimization functionalities for the replies of interaction and incorporation from the real-time atmosphere surrounding RIS for controlling and optimizing the reconfigurable panels and elements. Compared with the conventional ML, FL is inherently conductive to offloading computer-intensive tasks from the central server to the edge devices. Later we describe deploying an RIS in a harsh radio environment, which motivates us to leverage the RIS-based FL framework to configure the wireless propagation for processing of real-time data by making full use of the dispersed computation resources at the network edge.

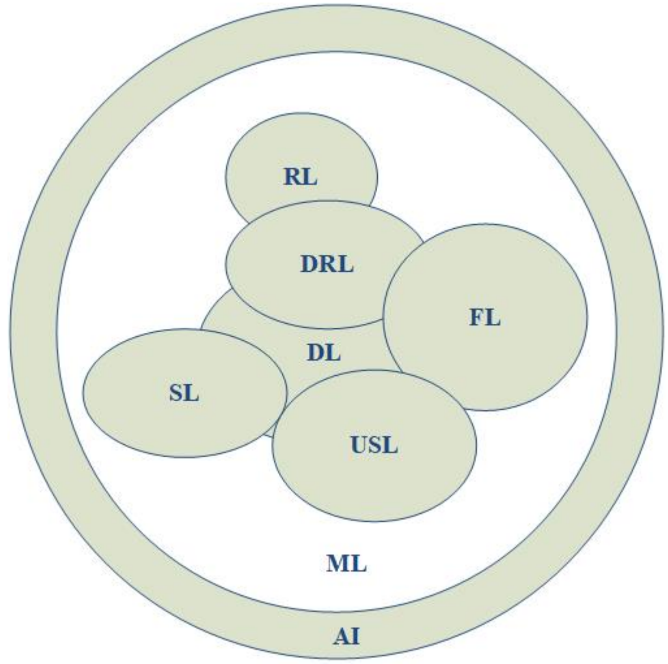

Fig. 18. Relationship among AI, ML, SL, USL, DL, RL, DRL, and FL.

2) FL techniques: FL is thought to be crucial in wide-scale ML as well as dispersed optimization based systems as it directly inspects the training statistical frameworks on distant devices [12]. Though the private information is still inaccessible, it does not impact the performance due to the nature of training at the edge of dispersed systems. The privacy-ensuring characteristics of FL-based procedures make them suitable for IoT networks in a distributed learning fashion, train their produced information and lastly transmit their native constraints towards the aggregating unit. Hence, the effective placement of RIS-based IoT networks faces challenges from system features to performance optimization. In order to decrease propagation error and signal distortion, then multi RIS-based IoT networks are essential for achieving a better convergence rate and lower learning error. Fig. 18 represents the association between AI, ML, USL, SL, RL, DL and FL. Nowadays, the standard ML techniques are based on a centralized concept, where the data are uploaded and processed on a single entity, e.g., a central server. Besides, FL considers the decentralized approaches where devices collaboratively train a model by leveraging their local computational resources. Furthermore, some ordinary benefits can be obtained through FL methods including hardware resources reduction, training quickness improvement, and user confidentiality enhancement. By adopting dispersed training, FL is capable of generating universal models using the federated averaging process where there are three distinct stages in the functioning procedure,

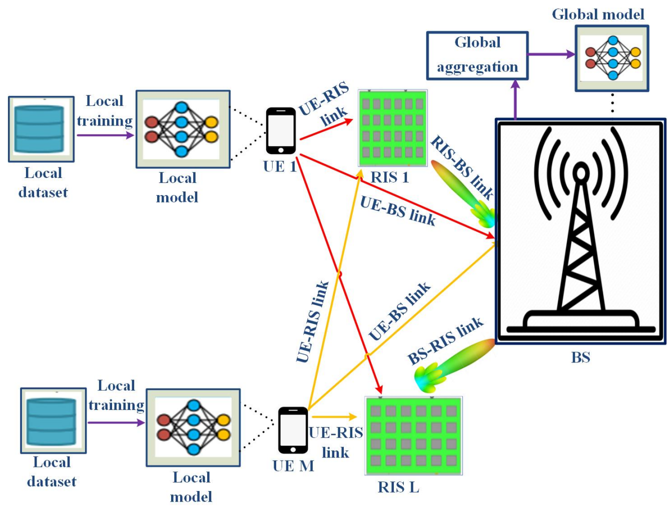

Fig. 19. A diagram of FL in multi-RIS assisted cellular networks [106].

such as native training, modernizing universal model, and universal aggregation, as presented in Fig. 19. At first IoT devices train their native model that are then used by the aggregation server to upgrade the universal model. The native and universal models upgrade frequently by maintaining periodic communications till reaching the agreement of the universal model. The sequential stages of every learning cycle shown in Fig. 19 are explained as below:

- **Local model upload:** Every IoT device upgrades its native model by employing learning methods and considering the latest downloaded universal model. Through virtual uplink communication, the upgraded native model is transmitted to the aggregation server for upgrading the universal model.
- **Global model download:** The aggregation server upgrades the universal model by aggregating the native models received from several specific IoT devices. Through virtual downlink communications, the upgraded universal model is transmitted to those devices for further improvement of native models.
- **Global Aggregation:** Considering the FL's efficiency optimization algorithm, an updated global model is estimated by the central server through the aggregation of the latest models received from the client UEs.

Each IoT device can collect an extremely small amount of data that is not enough for training a highly efficient AI model. FL learning techniques can overcome this limitation by training a universal AI model with the assistance of a large volume of confidentiality-required data from various IoT devices of a smart IoT network. As a result of offering a number of benefits, federated ML is considered as an efficient technique for manipulating the communication and computation resources through direct extraction of intelligence from UEs which reveals the ML proficiencies properly within a smart IoT network.

Applications of FL: Though all of the possible FL utilization sectors are not investigated yet, some main implementation scopes in 6G communication are explained below.

- **Smart grids:** Smart grids support data and power transmission in both directions in communication and electricity networks respectively, which incorporates the RIS assisted two-way flow of power and data, facilitating the active participation of all users in the energy management, the realization of lower power ingestion, higher confidentiality, auto-recovery and so on. Using this system, vast scale data production and processing can be done, however, central processing and storing are challenging [107]. Though there are a lot of advantages of intelligent electricity networks, a risk of data secrecy may arise while transferring them between the end users and cloud. Repetitive native data processing can assist overcoming this issue through the use of FL-empowered intelligent meters and aggregators at end devices as well as the results can be exploited universally [108]. Moreover, authors in [6] applied FL within a power grid mobile edge computing atmosphere in which a real-time UE choosing optimization procedure considers the trustworthiness of time-changing connection. In addition, RIS-enhanced FL method in IoT network is crucial for reducing the power requirement of electronic vehicles.
- **Unmanned mobility:** 6G communication system is expected to support driver-less autonomous vehicles demanding strong adjustment between those vehicles that can be fulfilled using ML frameworks. Several important aspects such as Cooperative unmanned driving, accident prevention, obstacle identification and traffic jam controlling need to be considered to establish an efficient self-directed vehicle system. In general, the ML frameworks are centrally trained in the cloud using off-line approach but these are unable to adopt dynamic variations of the system. In the dynamic changing wireless channel situation, RIS assisted FL can track the real time po-

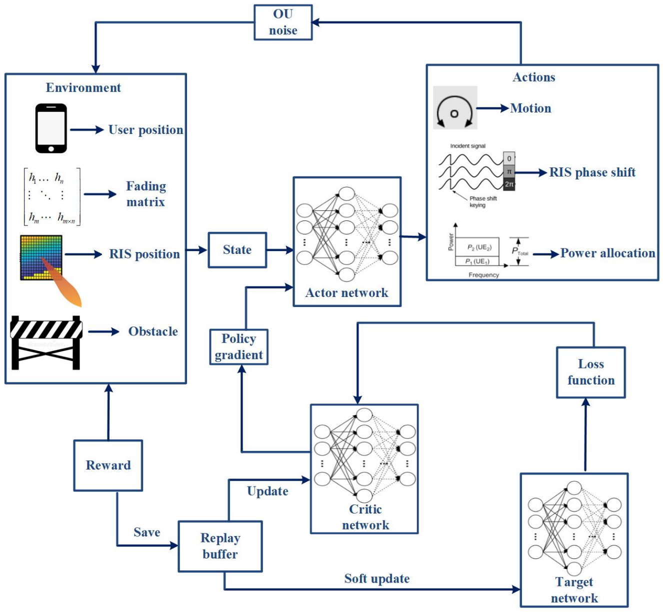

Fig. 20. Diagram of FL-DDPG algorithm [129].

sition of every vehicle by monitoring the circumstance updates which also help other vehicles providing more atmospheric information [110]. As a result, it can be confirmed that RIS enhanced FL technique is capable of reducing data traffic which is vital for latency-critical applications like unmanned vehicles.

- **AR:** AR is considered as an auspicious technology to realize interactional features through the combination of simulated substances with tangible elements [111-112]. Conventionally, AR models are trained in a centralized manner. However, the latency-sensitive AR applications enforce new challenges, while the centralized ML approach becomes non applicable. Consequently, RIS assisted FL technique decreases delay while detecting objects and performing classification problems. [113] proposed a joint approach using RIS based FL and mobile edge computing (MEC) for exploiting the computational abilities of end devices and reducing the energy requirement while implementing FL.

C. FL-DDPG algorithm for RIS assisted wireless networks

As obstacles that impede the movement of RIS and shields, LoS links are probable to have irregular and non-analytic shapes, which increases challenge for the classical optimization methods. Also, in contrast to convex and non-convex optimization, FL-DDPG is considered a promising approach for dynamic optimization difficulties, as DRL can identify the present state of the radio environment. The FL-DDPG is a distributed learning framework to utilize wireless computational resources that can improve the efficiency of exploration and training to explore the radio environment simultaneously. Their knowledge can be transferred to each other through a global neural network (NN) model.

In order to enhance the received SINR in indoor communication environment, a DNN-aided method was applied in [114] to estimate the coordination among RIS configuration and user location. Moreover, this NN technique demands longer time to train data that is hard to reduce due to the complexities of utility function optimization and the gigantic size of the relevant parameters. Besides, traditional iterative approaches are not suitable for SDM-based systems as they increase latency during training these models. To optimize the deployment and phase shifts of the RISs along with the corresponding transmission power allocation strategy for the UEs in every cell. In [114], the authors proposed an FL-DDPG-based technique where the realization of numerous improvements of the main DDPG method [115], i.e., adaptive NN structure and decomposing Ornstein Uhlenbeck (OU) noise to incorporate the technique. Besides, there are native agents installed in the AP that regulates the RIS actions as well as the carrier robot through the control channel. Additionally, this actor-critic framework employs four distinct sorts of neural networks, such as critic network, actor network, critic target network, actor target network within the DDPG agent. The actor network estimates and executes the action A^t by analyzing the network state S^t, which updates the state to S^{t+1} and determines the reward R^t depending on the required QoS and data-rate. Fig. 20 illustrates the updating procedure for a particular DDPG agent. The proposed algorithm trains the agent by incorporating the decaying OU noise from a noise process M to our actor policy which is given as

$$A^t = u(S^t|w_u^t) + M(0, \upsilon^t), \upsilon^t = \upsilon^0 \to 0, \upsilon^0 \in [1, 0), \quad (5)$$

where w_u^t and υ^t denote the parameters of NN and the scale of the OU noise, respectively. Moreover, M is a random process increasing the exploration through the stochastically perturbed actions, which adds two noise inputs. These inputs are composed of Gaussian noise and OU noise which are designed to make the learning process of UEs have higher randomness, avoid falling into local optimum, and improve the exploration efficiency of UE. Besides, υ^t is a random noise with a mean of 0 and a variance of 1. Every local agent set up its local model w_u^t and employs its individual computing wireless resources to train the model of local training, where u and t denote the agent number and time, respectively. The agent records and stores the transition (S^t, A^t, R^t, S^{t+1}) for every stage into a replay memory buffer and randomly samples experiences at every stage and trains NN according to the samples.

The DDPG algorithm maintains a parameterized actor function $\mu(S^t|w_u)$ which specifies the current policy by deterministically mapping states to a specific function. The actor networks can be updated following the policy gradient (PG) by applying the chain rule to be expected return from the start distribution J with respect to the actor parameters. Supposing the minibatch has e transition samples, the parameter updating of policy network by DDPG through the gradient $\bigtriangledown_{w_u} J$ is

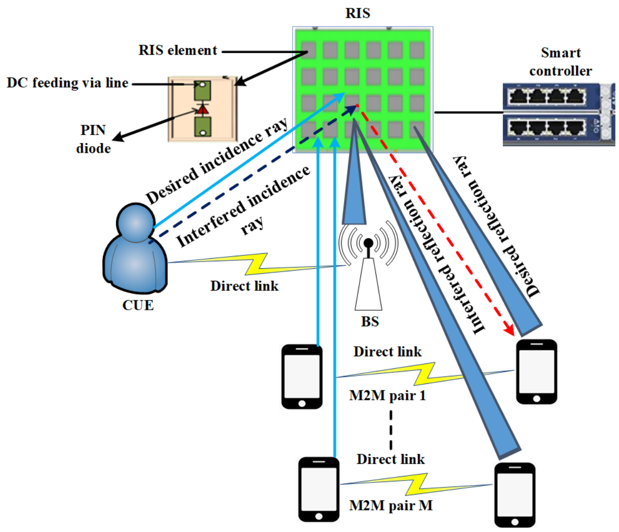

Fig. 21. RIS based M2M communications.

expressed as the following formula

$$\bigtriangledown_{w_u} J = \frac{1}{e} \sum_{e} \bigtriangledown^{A} Q(S^{t=e}, A^{t=e} \mid w_Q) \bigtriangledown_{\mu}^{w} \mu(S^{t=e} \mid w_{\mu}), \tag{6}$$

where e, w_Q and w_u represent the number of samples in the experience pool, actor and critic network weights, respectively. Moreover, $\bigtriangledown^{A} Q(S^t, A^t)$ is a sort of critic, telling the actor in which direction to change its policy: towards actions associated with more reward. A Q-value with a concern of long-term reward in the critic network utilizing transitions which are created from a diverse stochastic behavior policy β. Then, it is defined using the Bellman equation

$$Q(S^t, A^t) = R^t(S^t, A^t) + \beta max Q(S^{t+1}, A^{t+1}). \tag{7}$$

The critic network updated according to Q-value by lessening the loss function is given by

$$L^e = \frac{1}{e} \sum_{e} (y^{t=e} - Q(S^{t=e}, A^{t=e} \mid w_Q))^2, \tag{8}$$

where

$$y^t = R^t(S^t, A^t) + \beta Q'(S^{t+1}, \mu'(S^{t+1} \mid w_{\mu'}) \mid w_{Q'}), \tag{9}$$

and w'_Q and w'_u represent the actor target network and critic target network weights, respectively.

D. Architecture of ML-empowered RIS-enhanced M2M communications

RIS based M2M communications: M2M communications is a significant method to upgrade the system efficiency through the improvement of EE and spectrum efficiency (SE) and reduction of delay in future generation networks. Though the present studies mostly concentrate on optimizing the channel allocation and transmission power only [116]-[117], the resource sharing issue should also be investigated to mitigate interference in M2M communications [118]. Fig. 21 considers a cellular user equipment (CUE) and several M2M user equipments (MUEs) for uplink data transmission in a single cell based RIS-assisted heterogeneous network where RIS consists of a lot of configurable components having reflecting characteristics. In RIS-assisted Tx-Rx communication, the uplink channel is thought to assist numerous M2M multiplexing. Hence, the channel quality of cellular communication is weak when CUE is located far from BS. Moreover, various MUEs share different frequency band with the CUEs. However, RIS assisted M2M communications improve the received signal via M2M links. According to the regulation voltage, a certain phase shift will be provided by the metal plate. A new approach can jointly allocate radio resources and configure multiple distributed RISs for the uplink of a M2M-underlaid cellular system, where the RIS is deployed at the centre of the cell to improve propagation.

With reconfigurable characteristics, the propagation environment can be manipulated to alleviate interference between links and enhance the system performance. It reflects the signal from the Tx and maps to the Rx with directional beam. Via the help of RIS, the virtual link between the Tx and Rx is established. After that, the reflector sends the compound signals towards the intended Rx device just like a virtual source which incorporates the joint power allocation design and RIS phase shift optimization problem to maximize the system sum rate under the individual QoS, power and practical discrete phase shift constraints which subject to the power limits and QoS of the users [48]. To address the non-convexity of this problem, a new block coordinate descent (BCD) framework which decouples the M2M-CUE pairing, power allocation and receive beamforming, from the configuration of the RISs. As a result, the proposed algorithm can significantly improve the sum-rate of the M2M underlaid system with a reduced complexity. Also, in multiuser (MU)-M2M communications, especially for massive MIMO, the Tx with an antenna array can serve numerous UEs concurrently by utilizing multiuser spatial diversity with multiuser beamforming or precoding. For RIS-assisted MU-M2M communications, it is clear that with multiple RIS's, the spatial diversity among UEs can be enhanced. However, with a single RIS panel, designing an efficient RIS to increase MU-MIMO performance is difficult as the transmit-RIS path is the same for all UEs, especially for rank-deficient LoS channels between the Tx and the RIS. Therefore, the joint design of RIS and transmit MU precoding is crucial. Moreover, the joint symbol level precoding and reflection coefficients design is deemed for RIS-assisted MU-M2M communication systems to reduce the transmission power with assured QoS.

RIS-enhanced single-channel multi-user (SCMU) M2M communications is shown in Fig. 22 (A) wherein the RIS viewed as an entire unity can be reserved by one MUE to support the multiple data transmissions, thus achieving high efficient RIS-enhanced connections at the M2M user. Moreover, under frequency-selective channels, implementing the multi-dimension reservation (MDR) scheme on the RIS group division, RIS-enhanced multi-channel multi-user (MCMU) M2M

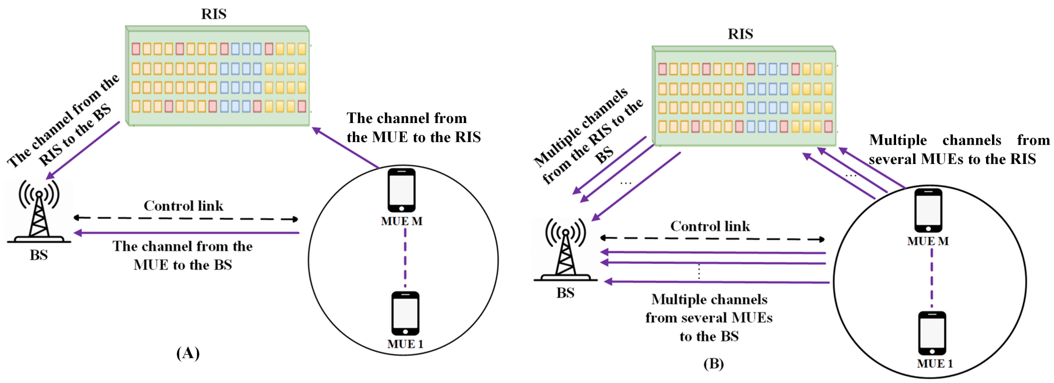

Fig. 22. RIS-enhanced SCMU/MCMU M2M communications.

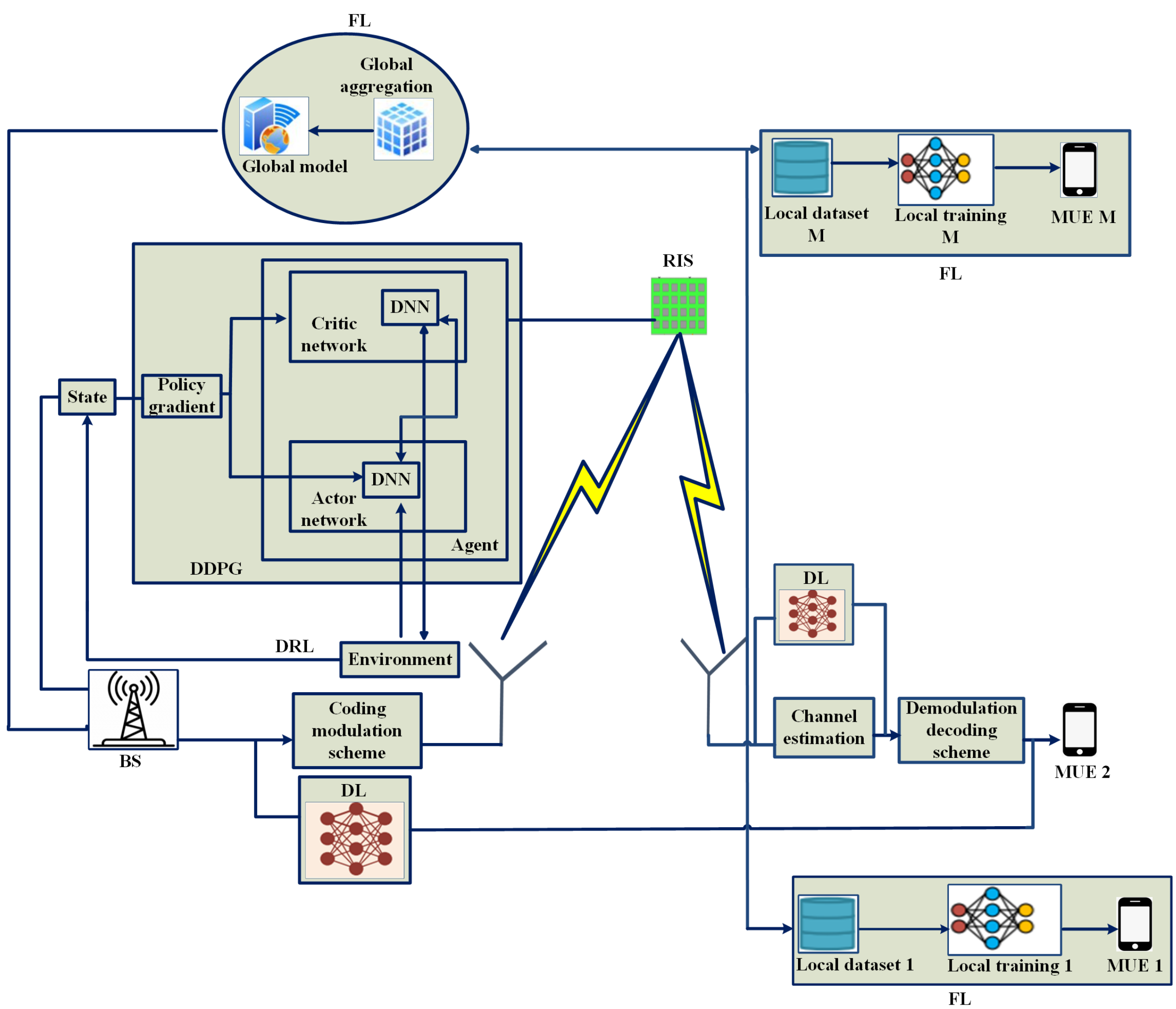

Fig. 23. Architecture of the ML embedded RIS-assisted M2M communications system.

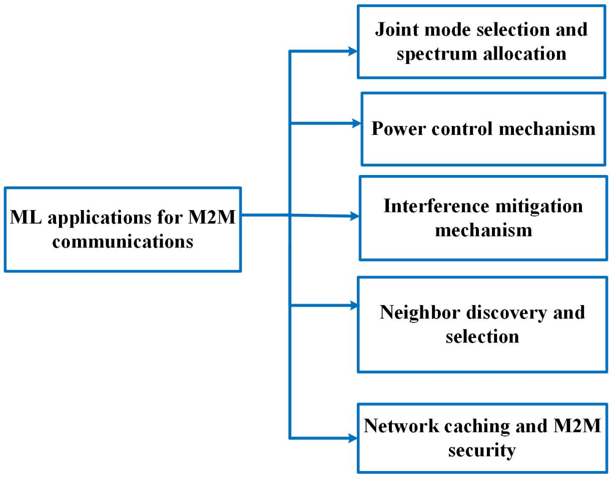

Fig. 24. ML applications for M2M communications.

communications is shown in Fig. 22 (B) which improves the service efficiency of the RIS.

ML-empowered RIS-enhanced M2M communications: Some investigations considered the rapid changing nature of wireless channels and proposed a number of communication atmosphere optimization techniques. Besides, a noticeable increment of the amount of training constraints happens since the DQN-enabled solutions typically utilize completely linked layers in the place of convolutional layers [119-120]. The rationale behind using these approaches is that knowledge from learning domain could be exploited in another domain without the need to redefine or retrain the model from scratch; this approach has been successfully employed for data correlation aware resource allocation problem. Therefore, DQN-integrated CNN and FL based DDPG are capable of optimizing the location and RIS phase shifts that reduce the parameter amounts as well as computational complexity. Fig. 23 presents a ML and RIS-aided M2M communications network which performs beamforming design, channel approximation, and signal identification in its physical layer but the virtual computation and resource distribution are done in the higher layers. Besides, ML applications for M2M communications are illustrated in Fig. 24. Moreover, this network achieves superior system efficiency as the RIS controller can learn the optimization policy of the deployment location and RIS phase shifts through the reception of real-time feedback and cooperation with the communication atmosphere.

In [121], the authors leveraged and modified two multi-armed bandits (MAB) based algorithms, namely, Kullback Leibler upper confidence bound (KLUCB) and minimax optimal stochastic strategy (MOSS) to formulate the gateway UAV selection issue. The issue is modeled as a budget-constrained multiagent MAB (MA-MAB) that maximizes data rates while considering UAVs' flight battery consumption. [122] has introduced RL-based latency controlled M2M connectivity (RL-LCDC) algorithm and its Q-learning approach in an indoor M2M communication network for strong 5G connectivity with minimum latency. The proposed approach, RL-LCDC efficiently discovers the neighbors, decides the M2M link, and adaptively controls the communication range for maximum network connectivity. The complexity of the mode selection and resource allocation (MSRA) problem has hampered the commercialization progress of M2M communication in 5G networks. The authors proposed an online learning technique (i.e., CBMoS) which leverages combinatorial multi-armed bandits (CMAB) to tackle the combinatorial nature of MSRA in [123]. A resource allocation deep autoencoder network is one of the promising generative models for enabling spectrum sharing in underlay D2D communication by solving linear sum assignment problems (LSAPs). The performance of three different architectures for the conditional variational autoencoders (CVAE), such as the convolutional neural network (CVAE-CNN) autoencoder, the feed-forward neural network (CVAE-FNN) autoencoder, and the hybrid (H-CVAE) autoencoder were investigated in [124]. Aiming to solve the most challenging radio resource management problem in D2D networks, [125] proposed a new transmission algorithm for D2D networks based on DL with a CNN. A CNN was formulated to yield a binary vector indicating whether to allow each D2D pair to transmit data from a suboptimal algorithm. D2D technology in cellular networks can improve the performance of cellular systems but it creates a large amount of interference in traditional communications. To reduce the complexity and interference intensity of resource allocation using K-means clustering algorithm, the concept of a restricted D2D communication area and a restricted D2D user-reusage area was put forward in [126]. Some researchers focused on time slot distribution to broadcast address information for discovering proximity devices. Moreover, other researchers pay attention to user grouping with different beacon probing signals. However, these peer discovery mechanisms do not consider the risks that source devices may encounter malicious devices in real situations. The peer discovery mechanisms were proposed in [127-129] which contributed to encountering malicious devices and enhanced the efficiency of peer discovery by excluding malicious devices using a modified Thompson sampling (TS) and variants of upper confidence bound (UCB) based algorithms assisted by MAB and DL techniques. However, since the same resources are shared by both M2M and conventional communication systems, interference, traffic burden as well as delay are several major challenges. Therefore, power control (PC) was needed to control the above-mentioned challenges which adopted ML algorithms like distributed Q-learning and CART Decision Tree in [130], SL algorithm in [131], DL algorithm for IoT networks in [132], DQN algorithm where the energy harvesting (EH) and channel gain processes was unavailable in [133]. D2D caching policies assumed perfect knowledge of the content popularity distribution. Since the content popularity distribution was usually unavailable, multi-agent RL like multi-agent MAB problem and Q-learning algorithm were applied in [134] to overcome those problems. Traditional device authentication is the cryptographic mechanism and the security protocol that

TABLE VII
SUMMARY OF THE RELATED WORKS THAT ADDRESS THE ML BASED M2M COMMUNICATIONS.

Ref.	Network category	Mode	Learning mechanism	Key contributions	Limitations
[121]	UAV-aided cellular networks	Multi-agent	Multi-armed bandit (MAB)	Explore UAV selects appropriate gateway UAV using ideal mmWave connection	Self-centered strategy cannot lessen collision
[122]	M2M communications over cellular networks	Single-agent	Q-learning algorithm	Optimum connectivity having little latency	Single-agent oriented RL technique
[123]	M2M communications over cellular networks	Multi-agent	DQN algorithm	Developed method provides high speed of learning and superior efficiency	Requires update of learning constraints tuning process based on the network condition
[124]	Underlay D2D communication	Multi-agent	Auto encoder and DNN algorithm	Almost optimum correctness with reduced complexity and lesser time	Efficiency fall at vast amount of connected devices
[125]	Mobile D2D Networks	Multi-agent	CNN algorithm	SE enhancement and cross-tier interference mitigation	Unsuitable for real-world spatial and mobile models
[126]	Full duplex based D2D communications	Single-agent	K-means clustering	FD system efficiency enhancement and interference reduction	Multi-cell consideration needed
[127-129]	D2D communication systems	Single-agent	MAB, DL	Neighbor discovery using mmWave in D2D network	Inappropriate for more than one device
[130]	D2D communications over cellular networks	Single-agent	Q-learning and CART decision tree algorithm	Interference mitigation	Non-cooperative multiple agent
[131]	D2D communications	Single-agent	SL algorithm	More capability deprived of data interchange among users	Unsuitable for multiple links among D2D pairs
[132]	IoT networks	Single-agent	DL algorithm	Fully automated power distribution in D2D- IoT communication	Avoids short scale fading and inappropriate for centralized architectures
[133]	Underlay D2D communication	Multi-agent	DRL algorithm	Wireless power control for massive energy harvesting networks	Unfit for distributed architectures
[134]	Mobile D2D networks	Multi-agent	Q-learning algorithm	Large average downloading latency and high caching rate	Optimal transmission range and number of neighbors are not considered
[135]	D2D communications	Multi-agent	SVM,CV-SVM	UE authentication and recognition	No inquiry on detecting diverse attacks

was not enough for the new security threat. That is why, Hilbert transform and principal component analysis was used to generate the RF fingerprint of D2D device using support vector machine (SVM) in [135]. The main limitations of ML based M2M communications discussed in this segment are summarized in Table VII.

E. Discussions and outlook

Smart radio environments are anticipated to witness a randomly evolving environment, as well as heterogeneous service requests, comprising different types of transceiver architectures, such as 1-bit digital beamforming, analogue beamforming and so on and RXs. An outstanding issue is how to deal with the heterogeneity of SDM environments and to effectively adapt to it without added complexity. ML techniques can facilitate solving a vast range of problems in intelligent IoT networks because of various capabilities of RISs, such as learning from the interaction with atmosphere and adapting the installation/controlling strategies considering user feedback for dealing with the uncertain/dynamic atmosphere. For gaining enduring advantages, RL models not only consider the present states, but also foresee the development of intelligent IoT networks. On the other hand, a sort of new issues will be introduced while enabling ML models, such as reward function production, state action creation of RL model, and layer design of DL model. Moreover, the collaboration between RISs make the simultaneous utilization of a number of RISs highly difficult, however, smart planning and installation of multi-RIS based IoT networks are extremely needed. In order to optimize the constraints of ML models, designing the continuous and discrete state spaces jointly instead of designing any one in ML and intelligent IoT networks is a promising research scope. Data- or model-assisted optimization methods are not reliable in intelligent wireless networks due to their huge volume of sensed data and extremely dynamic atmospheres. In this situation, for adaptive optimization of real-time network atmospheres, the software controller ML-aided SDMs can leverage transfer learning approaches through synergistic utilization of data- and model-driven approaches.

V. Incorporation of Emerging Technologies for ML-based Intelligent IoT Networks

Current investigation contributions have proved that ML empowered intelligent IoT networks are capable of obtaining adjusted channel gains, improved coverage range, enhanced QoS, and reduced energy consumption. These important performance improvements can be applied in IoT networks. In this section, we classify the main topics and investigation prospects on the path to 6G linked with the incorporation of developing technologies, such as NOMA, backscatter communications, STAR-RIS, PLS, CR, SWIPT, UAV, V2V communications and so on of ML-based RIS assisted for IoT systems.

A. Physical-layer security

As per investigation, RISs can concurrently enhance the preferred signal power propagated to the targeted UE and mitigate the interference power to the other UEs [90], [136]-[139], which motivated some researchers to explore the probable performance gain considering the PLS in intelligent IoT applications. In [140], the authors proposed RIS assisted secure wireless communications with MIMO antennas to maximize the secrecy rate by jointly optimizing the transmit covariance matrix at the access point and the reflecting coefficients at the RIS. In [141], the authors proposed an RIS-assisted secure MEC network framework to enhance the task offloading security by jointly optimizing the local computing frequencies and transmission power of IoT devices, time-slot assignment, and phase beamforming of the RIS. Signal quality can be improved using passive relaying of RIS which conversely decreases at the eavesdropper end. Since passive RIS does not produce synthetic noise, the signal quality reduction at desired location is done by other strategies. In IoT networks, various data-driven frameworks i.e. ML, RL, DL can be used to realize effective applications enabling flexibility and auto-optimizability [142]. The studies on the usage of ML-aided techniques in overcoming PLS issues within RIS-based networks are rare [143]. In Fig. 25, PLS improvement in intelligent IoT networks is shown where the attainable privacy communication rates are extremely short if the eNB-eavesdropper distance is less than eNB-legitimate user, or the eavesdropper and user both stand in similar direction. Additionally, effective reduction of data emission is obtained when an RIS and eavesdropper stay closer and the tune of RIS reflected signal neutralizes the eNB-eavesdropper signal. Therefore, in order to create an eavesdropper-prohibition zone by establishing a properly installed ML-empowered RIS-based secured region, the enhancement of privacy efficiency among the eavesdroppers and legitimate objects results in the increment of symbol error probability as well as failure possibility for IoT systems.

B. Unmanned aerial vehicle

RIS can even be applied to UAV-enabled IoT networks to improve wireless propagation environment and enhance signal quality, as shown in Fig. 26. The LoS associates between the UAV and the UEs may be congested, which worsens the signal quality. However, the RIS enhanced UAV communications can empower virtual LoS lanes via reflecting the received signal from UAV to the UEs. The received signal power at the UE can be improved by the combined UAV trajectory and optimization of RIS beamforming. Authors in [92], [144] improved the RIS phase shifts and UAV tracks at a time [145] where the use of RISs remarkably upgraded users' mean attainable data-rates [146]. Besides, UAV-assisted wireless relay networks can also be enhanced by the usage of RISs. In [147], researchers ensured wireless LoS links among user and eNB by modeling RIS reflection factors and UAV routes together in user mobility based RIS-assisted mmWave downlink transmission resulting in enhancement of per user data rate and of realizable downlink LoS likelihood. [148] approximated the instant SINR PDF and obtained the logical expressions of per-user capacity, symbol error rate (SER) and outage possibility within RIS-aided UAV relaying applications. A new RIS-assisted multiple UAV supported non-orthogonal multiple access (NOMA) communication structure was developed in [92], in which the installation of an RIS facilitated to improve the anticipated signal power among UAVs and relevant UEs by managing the inter-UAV interference. Furthermore, Liu et al. [149] included RISs in UAV-based radio networks in order

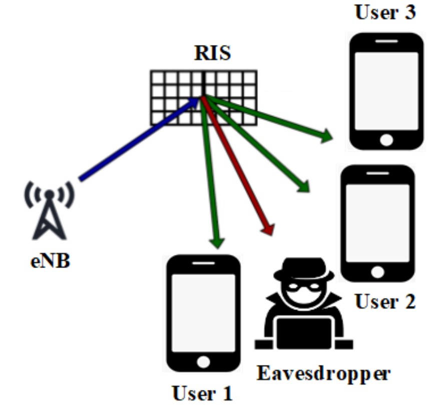

Fig. 25. Physical layer security [1], [14].

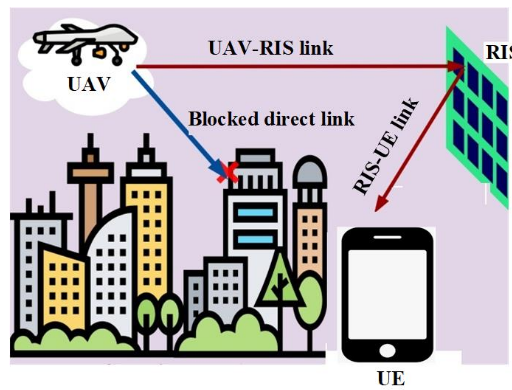

Fig. 26. RIS-assisted UAV communications [144].

to enhance the UAV's standard of service and reduce the power consumption. Since UAVs get power from batteries, further reduction of power ingestion is still challenging. Due to short flight durations, commercialization of UAV-based communications is hampered. For communicating with users via LoS links, RIS phase shift adjustment is better than UAV mobility controlling. If it is not possible to create wireless LoS links using RIS or any other means, the UAV can still fly perfectly. The utilization of above-mentioned strategies facilitate with minimum power requirement and more durable UAV. In addition, integrating a compressed wireless power transmission (WPT) Rx antenna or distributed laser charging (DLC) Rx enables the UAVs to acquire power supply until leaving the coverage area of the WPT/DLC Tx that is placed on the Earth surface or at rooftops [150]. Assured LoS links among UAVs and power supplying vehicles/stations is needed but skyscraping buildings in urban areas make it truly challenging. In this scenario, passive reflection based RISs can form LoS links to reconfigure the wireless communication atmosphere for not only UAV-UAV and but also UAV-charging station communications resulting in improved condition of charging service. ML-assisted extremely dynamic communication using RIS considers the UAVs' route model and the RISs' phase shift model for forming continuous and discrete state space respectively where simultaneous dealing with the state spaces is tough. In this circumstance, investigation on an ML-assisted RIS-aided smart UAV is of great significance for providing knowledge prediction and extraction, decision-making, and near-optimal optimization efficiency for IoT networks.

C. CR networks

To enhance SE and mitigate interference imposed by the secondary user (SU) TXs (SU-TXs) on the primary user (PU) RXs (PU-RXs), CRs allow spectrum distribution among SUs and PUs. Usage of beamforming can maximize the SUs entire-rate that also ensures to keep the interference of PU-RXs lesser than the interference temperature (IT) boundary. Unfortunately, the gain of beamforming becomes insufficient in the case of weak SU-Tx to SU-Rx link and extremely larger channel gain among SU-Tx and PU-Rx which can be handled by deploying an RIS near PU-RXs as shown in Fig. 27. Here, the RIS mitigates interference that affects PU-RXs, the use of RIS configurations by the PU-RXs can improve the task of spectrum sensing for the SU-RXs and improve the signal strength of SU-RXs. It is however worth noting that an increased detection threshold only indicates that the CR sensing node is willing to accept higher interference risk to the CR network. But, ML algorithms can learn the patterns from the structured training data with different features, such as power spectrum energy, waveform, modulation, and etc. through SL or USL methods. Based on the weights achieved from the training process, each node or the whole system can predict or conduct the corresponding spectrum decision. As a result, ML algorithm is essential to adopt in intelligent IoT systems for improving system performance.

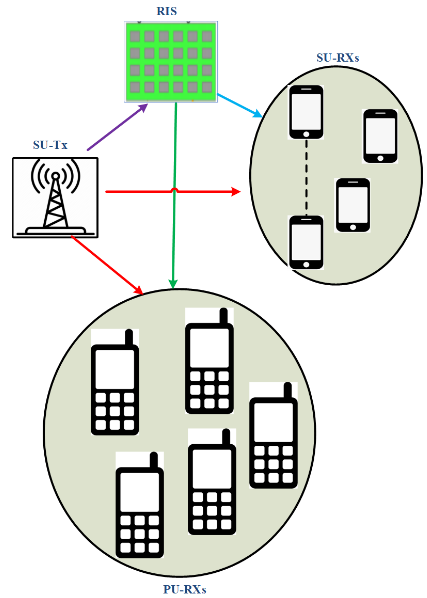

Fig. 27. RIS enabled cognitive radio networks [151].

D. SWIPT

SWIPT is a promising method for next generation IoT networks where poor EE is a major limitation which can be conquered using RIS. Considering the distinct required SINR of UEs, the authors in [152] analyzed the maximization process of weighted sum power received by energy RXs by joint optimization of transmit and passive beamforming along with AO-assisted procedure in RIS-aided SWIPT network. Besides, the maximization procedure of the smallest received energy among the power receiving devices was proposed in [153-159]. Additionally, several investigations found RIS to enhance EE in wireless networks [154], [155]. In [160], the authors investigated the total computation bits maximization problem for RIS-enhanced wireless powered MEC networks, by jointly optimizing the downlink/uplink phase beamforming of RIS, transmission power and time slot assignment used for wireless energy transfer and task offloading, and local computing frequencies of IoT devices. On the other hand, depending on the requirement of energy picking by every UE, authors in [157] explored the boosting process of weighted sum rate in RIS-aided SWIPT MIMO network where a block coordinate descent (BCD)-assisted procedure finds the Karush-Kuhn-Tucker (KKT) stationary spot. Moreover, a multi-RIS-assisted SWIPT system was presented in [154], in which the transmit power reduction increases the QoS of both the energy user (EU) and information user (IU). Various research papers found that the utilization of RIS can expand the virtual power transfer area as well as minimize the energy beam requirement. However, most of the related papers worked with performance gain in the context of RIS-aided SWIPT systems without taking RIS's EM features into account. In order to obtain the highest achievable conveniences from RISs, further investigations on EM-assisted advanced virtual energy transmitting

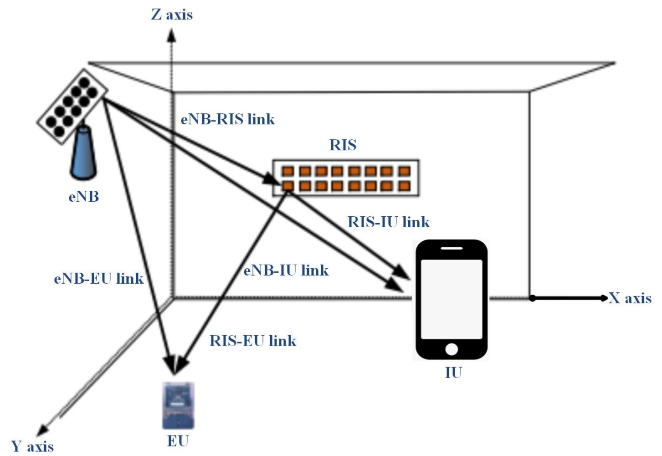

Fig. 28. RIS assisted SWIPT system [153].

designs are essential. Fig. 28 shows the application of RIS for realizing SWIPT to miscellaneous devices in an IoT network [153], where the large aperture of RIS is leveraged to compensate the significant power loss over long distance via passive beamforming to nearby IoT devices to improve the efficiency of wireless power transfer to them. Besides, RIS-aided SWIPT system can simultaneously transmit information and power to IU and EU, respectively. The intelligent IoT network is modelled as a function of the RIS reflecting coefficients and the coordinate of RIS. The RIS can harvest power from the received radio, where the harvested power can be adjusted by the amplitude of its reflecting coefficients. However, [154], has declared that the RIS-aided SWIPT and EH based systems are able to charge the low-power devices but self-charging of RIS is still a promising research topic that enables IoT devices to generate electrical energy by absorbing energy from the environment. This technology will overcome the replacement and maintenance of the batteries resulting in more reliable and long-lasting solutions. The EH method integrated extremely reflective surfaces look tough to design but an intelligent combination based reflective components' organization can be workable. Since some portions of the channel may require to be reflected to neighboring RISs for charging, the optimization issue for the passive beamforming, relaying, etc. turns more complicated than prior prediction. On the other hand, a green atmosphere can be obtained by unwanted radiation removal as a result of the surface's partial EM radiation consumption which is a significant benefit and motivates to design this type of low-power ML-based intelligent IoT networks.

E. STAR-RIS

STAR-RIS is able to transmit and reflect incident signals towards various directions from the RIS as shown in Fig. 29 and it has attracted both the researchers and industrial persons. The transmission user is located behind the STAR-RIS (i.e., transmission region), while the reception user is located in front of the STAR-RIS (i.e., reflection region). For transmission, the STAR-RIS allows the incident signal to pass through it via reconfiguring the signal propagation to the transmission user. For reflection, the RIS reflects and reconfigures the incident signal propagation to the reception user. Authors in [7] analyzed the prominence of RIS-adopted communication networks and reported a great improvement of EE and sum rate. Though most of the studies consider the RISs to be fully reflective metasurfaces while serving only the UEs on the same side of RIS resulting in limited efficiency [161], a proficient STAR-RIS based algorithm was recommended in [162] for overcoming the half-space coverage limitation. Moreover, [163] represents an effective model to verify the real-time implementation capability of STAR-RIS. Through the transmission and reflection of incident signals to both sides, STAR-RIS facilitates the realization of full-space coverage that is unavailable in traditional RISs. This upgraded degree-of-freedom increases pliability which can open a new era in designing next generation networks. Therefore, the utilization of STAR-RISs in future communication systems is of superior significance in terms of coverage. However, for conventional reflecting-only RISs aided secure communication, the legitimate users and eavesdroppers are assumed to be located at the same side of the RISs, even though this idealized simplifying assumption may not hold in practice. With the assistance of full-space STAR-RIS propagation, PLS can be enhanced, regardless of the eavesdropper location. For realistic multi-cell communication networks, the performance of cell-edge users cannot be guaranteed due to the strong inter-cell interference. Coordinated multi-point (CoMP) communication via STAR efficiently mitigates the inter-cell interference. In outdoor communications, similar to conventional reflecting-only RISs, STAR-RISs can be mounted on building facades and roadside billboards to create an additional communication link. More innovatively, ML-empowered STAR-RISs can also be accommodated by the windows of vehicles to enhance the signal strength received inside by exploiting their transmission capability.

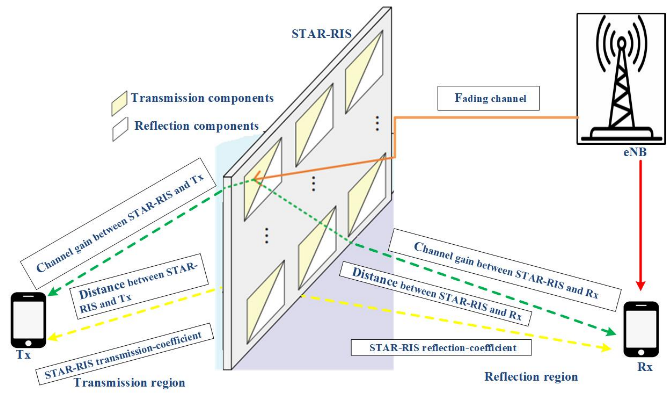

Fig. 29. STAR-RIS aided wireless communication systems [3].

F. NOMA

Power-domain NOMA technique can significantly enhance the UE connectivity and SE in intelligent IoT networks which

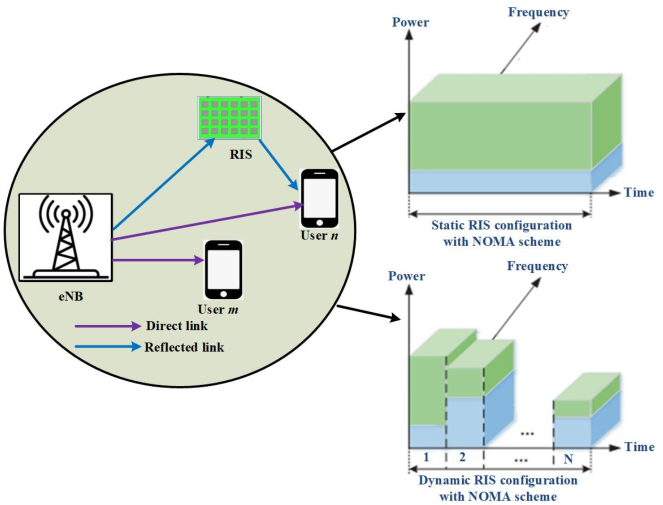

Fig. 30. Illustration of an intelligent IoT network employing NOMA scheme [166].

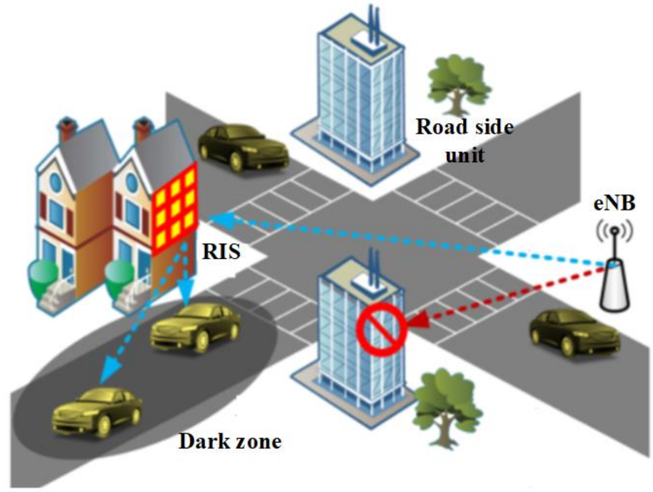

Fig. 31. RIS assisted V2V communications [169].

focus on covering numerous signals with dissimilar energies aimed at further SE through the practical investigation of various situations of channel [164]. In order to minimize the overall transmission power, authors in [165] designed a reflecting coefficients and transmit precoding vectors based joint scheme for MISO NOMA downlink wireless network. But integration of NOMA with RIS based systems impose different types of issues. For making highly-coupled combined beamforming models, user clustering, and decoding order models within RIS-NOMA systems, the decoding order among UEs and user clustering get affected by the passive phase shift modeling and active beamforming. In Fig. 30, NOMA technique is adopted in the intelligent IoT network which considers two types of RIS configuration process, such as static and dynamic RIS configuration. Consequently, RIS generates synthetic fading channels since the static and dynamic RIS configuration allow respectively one and N adjustments of RIS reflection coefficients in each propagation. The upcoming ML-aided NOMA-RIS networks are expected to consider multiple metrics while optimizing each factor, such as latency, capacity etc. Additional enhancement of ML techniques can be done by balancing the power, latency and capacity in the first stage and discovering the Pareto-optimal resolutions of the produced multi-goal-based optimization problems in the next stage.

G. V2V communications

RISs can also be deployed in vehicle-to-vehicle (V2V) communications as shown in Fig. 31, where the expensive onboard units (OBUs) are adjusted using vehicle-to-infrastructure (V2I) elements. Unfortunately, the complex road environments, difficult channel situation and rough weather conditions may cause degradation of QoS in existing V2I communication systems. A significant improvement in vehicular networks was presented in [167], [168] by combining RISs with present systems because EM material-made RISs are possible to place on various surfaces i.e. vehicle windows, building facades, advertising boards, highway polls and so on. Consequently, a huge amount of RIS placement can guarantee a more reliable wireless LoS link based V2V network. The main concern of intelligent autonomous driving systems is the driving security of autonomous vehicles (AVs) which actually means collision avoidance along with obeying traffic rules. In addition, guaranteed QoS of virtual AVs link is mandatory in intelligent V2I-aided autonomous driving systems. In this circumstance, reliability improvement of intelligent autonomous driving systems need more research attention to allocate spectrum efficiently using ML algorithms considering various types of traffic situations.

H. Backscatter communications

A backscatter tag reflects, and at the same time modulates, an incident radio signal without the need for power-hungry components in radio frequency frontends, e.g., carrier synthesizers and power amplifiers can be eliminated. For realizing superior EE, data rate, and reliability in IoT systems, backscatter communication can be a good technology to ensure ultra-low-cost and ultra-low-power. As it has been applied in small networks only, the massive-scale implementation challenges are still unknown. [170] explored biostatic and monostatic backscatter network with the use of RIS for tag-reader communication where a combined optimization strategy minimizes the transmission power as well as optimizes both the phase-shifts of RIS and the beamforming of Tx. Moreover, RIS is capable of transmitting signals to various directions which reduces interference significantly resulting in improved efficiency in ambient backscatter networks. Besides, [171] optimized the beamforming of the reader and RIS in an intelligent ambient backscatter network where no information regarding ambient signals and channels is needed. Furthermore, as per [170], RIS significantly improved the efficiency of signal detection in an RIS-enabled ambient backscatter network. However, due to the imperfect CSI and non-convex environment of optimization constraints, ML algorithms are

TABLE VIII

MAIN RESEARCH LIMITATIONS OF ML AND RIS-ENABLED IOT NETWORKS AND POTENTIAL SOLUTIONS EMPLOYING ADVANCED TECHNOLOGIES.

Challenges	Explanation	Potential solutions
Security and privacy	• The growth of IoT networks introduce new issues regarding confidentiality and privacy, e.g., illegal access to information at computing edges, integrity risks in radio access network architectures, and information splits in edge intelligence. • The implementation of satellite UAV-IoT data communications in unreliable space atmospheres can be interrupted by information privacy problems produced by illegal users and rivals throughout the information interchange and signal transmission.	• RIS enhanced FL algorithm can be useful to protect training datasets against data breach in the edge intelligence-based 6G IoT networks. • RLS enhanced PLS is a promising solution to build trust and establish secured decentralized communications for 6G IoT networks over the space and untrusted wireless environments.
EE	• Achieving higher EE in upcoming 6G enabled IoT networks is a vital demand, i.e., transmit power required for information exchange, M2M communications, and QoS. • Implementing energy-efficient radio communication protocols is extremely desired for green IoT-enhanced 6G networks.	• Joint optimization of the phase shift and position of RIS for improving the QoS and reducing the energy consumption in 6G-based smart automation systems, by implementing ML algorithms. • RIS enhanced EH schemes using SWIPT to employ the renewable energy resources will be more beneficial to build green IoT-based 6G networks.
Standard requirements	• The implementation of 6G-IoT networks need rigorous standard stipulations which calls the teamwork of each business stakeholder, i.e., telecom operator, internet service provider, and consumer. • The introduction of vertical 6G assisted IoT networks use cases in upcoming intelligent networks enforces key structural alterations to existing cellular networks to support a wide diversity of rigorous necessities.	• Establishing updated standards for computing and 6G server IoT device communication protocols based on ML algorithm using RIS. • Backscatter communication is crucial for leveraging seamless resources in various RIS based IoT applications using ML. • Modelling with multi-agents competitively collaboratively.
Hardware constraints	• The participation in IoT networks and computation tasks poses new challenges in hardware designs for IoT UEs. • Due to the constraints of hardware, memory, and power resources, certain IoT sensors cannot meet these computational requirements in IoT applications.	• SDMs based DL accelerator to support AI training on mobile sensor hardware. • It is crucial to develop lightweight on UEs hardware platforms to meet service computation demands in future IoT networks.

considered as a promising concept for RIS-assisted backscatter IoT systems because of their learning proficiency and huge search space. This appeals for efficient ML-based RIS-assisted backscatter to completely reap the potentials of IoT systems, such as environmental sensing, channel estimation, phase-shift design, and spectrum allocation.

I. RIS-assisted THz communications

A key enabler of 6G network is the utilization of ultra-wide bandwidth in RIS-integrated THz communication which can cover a large area but may be interrupted due to extreme attenuation problems. However, several issues such as reducing delay, handling exceptional transmission characteristics, and minimizing desired efficiency metrics should be investigated more to unlock the full potential of new hybrid ML-models that combine physical-models with data-driven learning approaches using RIS for THz communications.

J. RIS-assisted optical communications

Light fidelity (LiFi) is a promising technique that works according to visible light communications (VLC) and has the capability of conquering the NLoS effects in highly dynamic 6G networks. It is anticipated that RIS integrated LiFi systems are of superior significance because of assuring scalability and overhead degradation in real-time wireless communications. Moreover, space, traffic demands, computing energy, and memory are crucial parameters to be taken into account while configuring a programmable environment as well as managing the network resources. ML algorithms have potential to handle this challenging situation through the automation of operational, controlling, and maintenance related activities in LiFi based systems. Hence, more studies are required to find appropriate ML approaches for overcoming the limitations of current mechanisms [172-173].

K. Discussions and viewpoint

The survey of ML algorithms have revealed auspicious research prospects, such as PLS, SWIPT, NOMA, V2V, and UAV assisted intelligent IoT networks. Current investigation contributions have verified that intelligent IoT networks can attain improved network gains, boosted coverage range, enhanced QoS, and abridged power waste. However, the network and beamforming designs are extremely joined owing to vigorous control of the RIS phase changes that fetches challenges to these new investigation scopes. ML and intelligent IoT systems still need more investigations to provide better efficiency through the integration of advanced technologies. Table VIII provides the main limitations and further research scopes by incorporating ML-assisted RIS with emerging technologies.

VI. Resource Allocation for ML-based IoT Networks using RIS

Resource allocation has a significant impact on the design, deployment and resource optimization for wireless networks. Efficacious resource sharing systems assure more system efficiency, additional network linkage, and lesser energy ingestion. According to the previous description, RIS integration can upgrade the efficiency of IoT networks which motivates designing a joint transmit and passive beamforming along with appropriate optimal resource allocation making it essential for intelligent IoT networks. This section discusses the ML governed resource sharing approaches in intelligent IoT networks.

A. Traditional resource management in IoT networks

As the next generation wireless communication networks are complicated because of being exhaustive, multipurpose, and diverse, the optimum allocation and management of radio resource blocks turn into further complicated optimization problems which is aimed to attain a specific objective, i.e., maximizing EE, SE and network throughput by providing the accessible radio resource blocks and required QoS to users. But the huge diversity of future networks causes extreme complex issues while composing optimization problems and utilizing traditional methods for solving them, for example, heuristic, optimization, and game theory algorithms. Furthermore, due to being invented for uniform players, game theory-aided procedures do not fit the upcoming IoT networks. Additionally, the excessive traffic load created by the gigantic figure of UEs while communicating with eNBs will be uncontrollable resulting in more delay, additional memory/energy requirement and extra complex computation. The present spectrum sharing techniques will arise enormous limitations in next generation IoT networks in which the vital ones are discussed below [174]-[175]:

- Almost all current spectrum sharing methods need full or partial information regarding exact channel design and instantaneous CSI which is tough to acquire because of wide-range, high density, and extreme diversity of the network.
- The heavy system dependency nature makes these methods inappropriate for fast changing networks which requires the reconfiguration of reflection based future network surroundings. But current wireless systems have to adopt immensely real-time schemes maintaining high mobility in smart railway and vehicular networks. That's why the traditional methods become inappropriate in certain circumstances.
- As the spectrum allocation procedures are usually non-convex and complicated in IoT networks [176], therefore, grasping traditional optimization techniques will provide better outcomes in native optimal solutions, not in global solutions. This situation is very common in a lot of native goals based wireless optimization problems.

B. Advantages of ML based RIS-empowered spectrum sharing

Several promising AI techniques i.e. DRL, DL, and ML, are currently being implemented for proper limitation finding in various sectors of wireless communication networks, especially in spectrum sharing in CR network. In order to increase SE by developing smart and efficient methods, AI tools will be able to control massive information in future networks. In this paper, we survey spectrum sharing based DRL solutions for IoT networks. The recent research works assist the network regulators in resolving complicated network optimization problems using small amounts of data only. After learning the optimum strategies, DRL agents can be installed in an online environment, so that they can decide smartly and independently through native monitoring in wireless networks. Consequently, it can be summarized that, DRL scheme is essential for managing resources in four circumstances mainly;

- too little information available regarding wireless communication networks,
- lack of correct mathematical models,
- requirement of presumed data for incorporating the decision making procedure or existence of mathematical model,
- impractical implementation of traditional approaches.

Generally maximum spectrum controlling problems for IoT networks lie within the overhead circumstances. The core cause is the network's huge diversity and comprehensiveness according to the quantities and categories of UEs, relevant architecture, and QoS requirements. In this situation, the traditional methods will provide untrustworthy as well as inferior spectrum regulation and application. On the other hand, DRL methods are able to manage resources much accurately and reliably by adapting and learning the state of radio atmospheres actively. Due to the above mentioned exclusive characteristics, DRL approaches are considered as prominent AI-aided techniques which could be applied for managing resource blocks (RBs) within IoT networks. Several relevant present literatures are summarized in Table IX from which it can be observed that ML methods are effective in dealing with varieties of combined radio spectrums in wide network conditions by obtaining better outcomes compared to heuristic techniques [177] and comparable to recent optimization approaches [178-180]. In [190], the authors proposed a heterogeneous computation and resource allocation framework based on a heterogeneous mobile architecture to achieve effective implementation of FL. To minimize the energy consumption of smart devices and maximize their harvesting energy simultaneously by jointly optimizing the time splitting for wireless power transfer, dataset size allocation, transmit power allocation and subcarrier assignment during communications, and processor frequency of processing units (central processing unit (CPU) and graphics processing unit

TABLE IX
SUMMARY OF THE RELATED WORKS THAT ADDRESS THE RESOURCE ALLOCATION.

Ref.	Network category	Classification of cellular resource	Learning mode	Learning mechanism
[181]	Cellular networks	Spectrum and power allocation	Multi-agent	DDPG
[182]	UAV-aided M2M networks	Bandwidth, throughput and power	Multi-agent	DQN
[183]	M2M networks	Channel selection and power control	Multi-agent	DQN
[184]	V2V networks	Sub-band selection and power level control	Multi-agent	DQN
[185]	CR networks	Channel selection and power allocation	Single-agent	DDQN
[186]	NOMA systems for cellular networks	Subcarrier assignment and power allocation	Multi-agent	DQN and DDPG
[187]	Multi-carrier NOMA-based M2M communication systems	Channel assignment and power allocation	Single-agent	DQN
[188]	Cellular networks	Channel selection and power allocation	Multi-agent	DQN
[189]	NOMA assisted V2V networks	Spectrum and power allocation	Multi-agent	DDPG

(GPU)). However, in these contexts, numerous new investigation challenges emerge for the traditional ML process:

Challenge–1**:** Before training the local model at every iteration of the traditional ML process, the computing server initially needs to accomplish resource allocation (e.g., client's selection and spectrum allocation) via solving the corresponding convex and non-convex optimization problems. Due to the presence of shadowing and multi-path fading in wireless channel environments, several clients may unable to dependably transmit their radio channel information to the BSs via the M2M links that may be harshly degraded and become untrustworthy. In this case, the BS cannot act the resource utilization proficiently.

Challenge–2**:** In traditional ML, the clients who complete the training of local model for sending via wireless connections their local models to the BS for the aggregation of the global model. According to the probable untrustworthiness of the wireless M2M links and the limited frequency, the ML scheme's fast convergence may be degraded because of the low accuracy of uploading the local models. In this context, the efficiency of the ML forecast may be degraded since numerous local models may be obtained ineffectively radio channel information at the BSs.

Promising AI procedures, i.e. ML framework for RISs-aided cellular networks, expose significant efficiency while overcoming numerous limitations of up-to-date radio networks, which includes resolving complicated spectrum optimization problems [176]. Based on composed radio frequency data traces, the device trains their ML models and then uploads them to a computing server by RIS-enhanced wireless connections, thus attaining a quick yet aggregation of the reliable model. At the beginning of every iteration, besides, the aggregated model is placed at every smart controller to aid the BS to gather the requests of devices through cooperatively sensing the radio spectrum, thus increasing the network performance, particularly in complex shadowing fading and time-varying wireless propagation environments. Therefore, for overcoming the weaknesses and restrictions of the aforementioned traditional spectrum sharing methods, ML techniques can be utilized as they are able to decide without using vast data regarding the network state. For achieving numerous objectives i.e. throughput improvement, trustworthiness development, interval cutting, and EE/SE expansion, these techniques facilitate the network objects, i.e. eNBs, radio access networks (RANs), APs, edge servers (ESs), gateways nodes, and UEs by making smart and independent control decisions, i.e. spectrum managing, UE interconnection, and RAN's picking.

C. Information theory perspective

A number of investigations [191-195] have investigated the efficiency gains of RIS, considering information theoretic aspects for overcoming the basic RISs efficiency limitations. Authors in [192-193] studied the receptivity of a SIMO network which is based on RIS. In order to achieve the channel receptivity using limited input signal collections, a dual data encoding system is necessary at RIS outlines and dispatched signals [194] leading to a real-time communication approach through the utilization of layered encoding and continuous extinction decoding methods. In [195], the receptivity scope of the multiple access channel (MAC) having distributed and centralized RIS installation approaches based UEs was considered which shows that the centralized RIS installation approach achieves greater receptivity gain compared to the distributed approach. Randomly determined game theory-assisted DRL methods are considered as an auspicious research topic in next generation radio communication systems due to huge hybridity, UE amounts, and application diversities [193]. While allocating spectrum resources efficiently in IoT networks, the optimal stability among the distributed and centralized problem makes the development of DRL-aided methods challenging because of the uncontrollable data interchanging issue caused by rapidly increased edge devices (players).

D. Combined transmission and passive beamforming strategy

Fig. 32 represents an RIS-assisted communication among eNB and UEs through the passive reflection of signals where the eNB can adjust the reflection constants using RIS regulator which leads to a joint design of eNB's transmission beamforming and RIS's passive beamforming resulting in improved network efficiency. In [196], authors designed the costs to estimate channel and adjust RIS in which the EE maximization was done by joint optimization of RIS phase shifts and the transmitted and received filters in an RIS-employed MIMO network. Researchers in [197] proposed

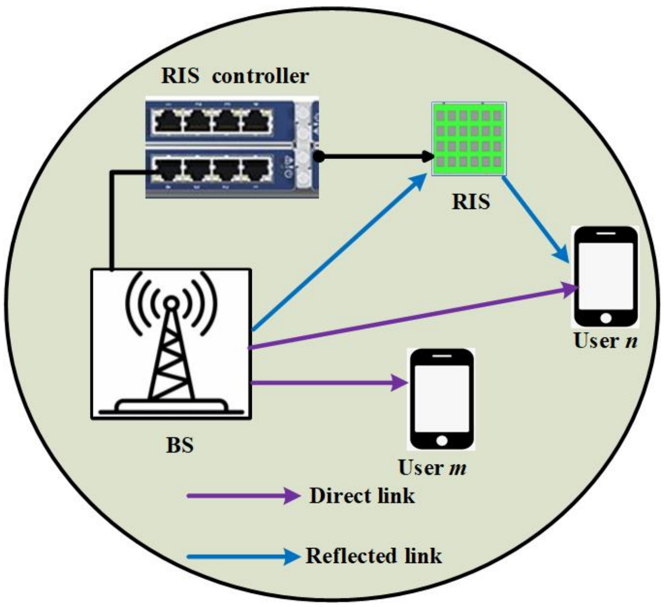

Fig. 32. Illustration of joint transmit and passive beamforming design.

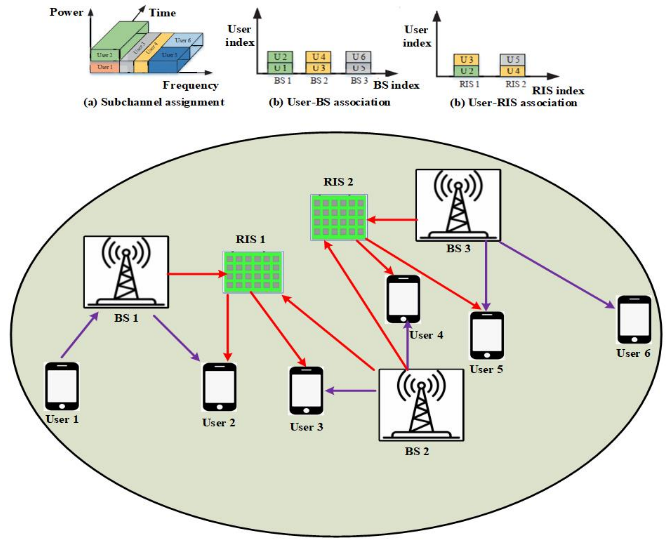

Fig. 33. Illustration of resource management in large-scale intelligent IoT networks.

a communication procedure that considers the channel approximation using distinct RIS phase shifts and reduces the corresponding errors by developing smaller complexity based discrete Fourier transform (DFT) - hadamard aided reflecting technique resulting in expanded attainable throughput. For reducing the complexity and cost of channel training, at first the statistical CSI optimizes the RIS phase shifts which along with the immediate CSI cooperates in designing the transmission beamforming in the next phase. Though IoT is being considered as a crucial term for next generation networks, several IoT devices have size and energy consumption related limitations. Upcoming wireless systems will use mmWave channels which demand highly directional antenna gains for achieving higher throughput. Also, mmWave bands consume more power and IoT are low powered. However, for communicating with far away eNB, extremely tiny shaped IoT devices will be unable to uphold the required antenna arrays for achieving sufficient beamforming gain. In this case RIS can offer more beamforming gain than they actually afford. As the eNB and RIS stay in a static location with fixed area coverage, beamforming optimization among them turns simpler. Thus in order to obtain vast IoT usage, the aforementioned issues can be overcome by combined ML methods using RIS of beamforming.

E. DRL for resource management in RIS-assisted IoT networks

Fig. 33 shows a wide-ranging intelligent radio communication environment which consists of a BS, users and RIS. The increasing amount of investigations have explored several benefits of RISs including the enhancement of EE, SE, and user fairness. But, the non-convex combined beamforming optimization problem was resolved in maximum recent research papers by applying the AO technique to create two distinct problems by separating the passive beamforming and combined transmission scheme. However it can provide a superior substandard result, but for characterizing the optimum efficiency gain presented by RISs, the latest optimization methods are needed to solve the problem. It also offers a major standard in order to verify the effectiveness of other poorly complicated substandard methods. Additionally, attaining exact CSI is truly tough in intelligent IoT networks because of the almost passive RIS functioning style. Moreover, the healthy dual beamforming planning and spectrum sharing is a vital research scope for implementing RISs practically [198-201] which needs developed spectrum managing techniques for optimizing system efficiency. By adopting E2E DRL-assisted methods, huge future improvements can be made in this sector for optimizing various RIS settings together, such as RBs of eNBs and amplitudes and phases of RIS components. In this situation, the development of DRL applications, which facilitates intelligent and optimal allocation of downlink eNB's transmission energy from one side as well as the amplitude and phase shifts of RIS components on the other side has been an auspicious investigation trend [200]. As per expectation, the present research works on intelligent IoT networks are going to be the foundation in this sector. The main limitations and further research scopes discussed in this segment are summarized in Table X.

VII. Future Research Directions

In this section, we highlight numerous interesting research challenges and point out possible future directions for ML-based intelligent IoT systems.

A. Federated DRL (FDRL)-based resource management

FL technique actually intends at preserving information confidentiality where ML procedures are natively circulated

TABLE X
SUMMARY OF CHALLENGES AND FURTHER RESEARCH SCOPES OF RESOURCE MANAGEMENT

Key challenges	Emerging ML can adjust the centralized and distributed way of resource management in upcoming large-scale IoT networks.
	Emerging further efficient and trustworthy training methods that produce exact numerical datasets and detect real-world system configuration.
	Planning agile DRL procedures that can rapidly modernize and train in the DNNs from the extremely dynamic network environment.
	Emerging DRL designs that are conscious of the background situation and use cases of numerous developing solutions.
	Developing DRL processes that adapt competing multi-purposes regarding emerging solutions.
Upcoming research directions	Emerging effective and trustworthy ML techniques for resource management in IoT networks based on entity identification, entity-relationship withdrawal, and depiction learning.
	Emerging combined learning techniques that guarantee universal applications for complicated spectrum optimization problems during data distribution and models modernizing.
	Emerging DRL designs to realize smart load adjusting in upcoming self-supporting IoT networks.
	Emerging ultra-dependable resource management by mixing DRL methods to uphold developing IoT solutions with high-dependability requirements.
	Emerging E2E ML-aided methods that together improve the organization of RIS schemes, i.e., components' phases and amplitudes, and radio spectrums of networks, such as downlink transmission power.

in the IoT network terminal, and the information processing occurs in the local area only which is further applied on the central universal training framework. Adaptation of federated DRL learning (FDRL) system in this environment facilitates numerous wireless UEs to locally decide independently but a DRL agent doesn't share native decisions with others and also all the agents don't get reward signals [202-204]. However, in the case of small state areas and limited training datasets, the development of excellent DRL strategies is tough [205]. In addition, direct information interchange among agents is impossible in FDRL systems due to security issues, thus, native DRL frameworks are required to develop and train the agents using other agents' assistance while ensuring users' information security [206]-[208]. So, developing algorithms and schemes that guarantee data and models privacy during both information sharing and model upgrading in IoT networks can be a promising research opportunity. Moreover, several complicated IoT network optimization problems, such as power controlling in wireless UDNs can be solved using this approach where RIS enhanced FDRL algorithm ensures universal resolution preserving data confidentiality.

B. ML-empowered RIS-assisted backscatter communication

Since optimization variables are non-convex and inadequate CSI, ML-based frameworks can be applied in RIS-empowered ambient backscatter networks because of being able to learn and search extensively. Also RIS- and ML- aided backscatter networks provide better system performance in [171] than traditional signal processing and optimization procedures in terms of resource distribution, RIS phase-shift design, channel approximation, and environmental sensing. Therefore, the utilization of ML frameworks in unlocking the full potentials of RIS-based backscatter networks is of superior significance.

C. ML-based asynchronous communication

During implementing FL, communication congestion is considered as a key limitation as it increases latency. According to the principles of traditional synchronous communication, the slowest UE defines the latency as well as the convergence rapidity of the framework. If any UE cannot complete its task, the whole framework remains stuck at a point. Asynchronous FL can solve this type of problems which allows joining UEs in FL tasks at any time, even in an ongoing training cycle [209]. Consequently, this promising feature of asynchronous communication facilitates the utilization of FL using the RIS by enhancing the expandability in real-world systems. But the low-latency hypothesis is impractical in real-time FL systems, thus the development of RIS enhanced new asynchronous strategies is needed those will consider not only the nature of user but also the capability of completing the given tasks fruitfully.

D. ML for new physical layer

The potential M2M communications in 6G are expected to provide a large number of data services which need the integration of waveform, modulation, coding, and multiple access techniques. Thus, the development of adaptive PHY is really needed for accommodating different use cases as well as their technological necessities. High mobility in future networks may provide inaccurate channel estimation because of the rapid channel fading caused by large Doppler spread. Extremely dynamic networks make the channel situations more complex, therefore, linear minimum mean square error (LMMSE) estimation cannot yield optimum efficiency. In typical approaches, the CSI estimation and transmitted signal recovery activities are done sequentially, which produces large delay in the Rx end [209-210]. In this circumstance, ML can enhance the channel estimation in upcoming 6G-V2X systems. [211–213] optimized the channel estimation using DL where offline training is implemented for reducing the training time and handling huge data. However, efficiency fall may happen as the considered channels are not fully similar to the actual channels [214]. Hence, the way of efficient channel approximation in extremely dynamic networks requires more investigation. ML has the potential for optimizing numerous configurations simultaneously, such as ML-enabled adaptive coding and modulation (ACM) using RIS can remarkably reduce the transmission delay and improve robustness. Therefore, considering the complete E2E physical layer architecture, further studies on ML-assisted dual optimization are highly needed for intelligent IoT network.

E. QML for cellular communication systems

The emerging paradigm of quantum machine learning (QML) is receiving significant attention, since it is showing great promise for various applications in current and emerging communication networks, like SDMs [215]. QML offers benefits of scalability, faster training and inference speeds, and reliability in comparison to conventional ML approaches due to the inherent parallelism offered by the fundamental concepts of quantum mechanics. Unlike conventional RL algorithms, which suffer from slow convergence time, quantum-powered RL leverages the superposition and parallelism concepts of quantum mechanics to speed up the learning, as discussed in [215]. Notably, the crossover between quantum communication and DNN is an interesting area which researchers have started to explore, and has remarkable scope for unlocking the full potential of SDMs.

PLS based on classical key distribution schemes, such as Diffie-Hellman [216] are also not secure, meanwhile, its security has relied on the assumption that the computationally complex problem of the discrete logarithm cannot be solved in realistic time through classical computers. Maximum existing cellular quantum key distribution systems are point-to-point (P2P) connections (i.e., satellite-to-earth connections) implemented by utilizing optical frequencies [217]. This needs huge precision tracking of the destination and does not support the high mobility essential for terrestrial 6G wireless applications. This is a challenge that imposes the real implementation of large-scale QML models, a complex task for uncontrolled radio propagation.

However, the RIS-assisted QML framework paves the way for incorporating quantum UEs with quantum data with existing cellular networks. Consequently, we expect that this can impose a blooming of new wireless applications that are joined with new investigation issues in the areas of cellular networking, quantum hardware, and wireless sensing. This is a high breakthrough that permits leveraging the potent computing capabilities of quantum computers in nowadays wireless networks to overcome the computational optimization complexity. The RIS-assisted QML framework enables training of the QML models inside forthcoming 6G wireless networks which is very promising to accelerate data processing speeds. Lastly, so as to add a new layer of security to the RIS-assisted QML framework, one can explore the employ of quantum cryptographic methods to encrypt the classical learning constraints in the QML setup before transmitting them to the computing server, and vice versa. As the client has quantum capabilities, incorporating QML with RIS is an interesting challenging problem that is valuable for investigation in the forthcoming in a low-latency fashion. Then, it is a critical metric for enabling the real-time adaptively of RIS functionalities for QML-based cellular communication systems.

F. FL-empowered RIS-assisted semantic communication

Shannon and Weaver first introduced semantic communication in their landmark paper [218]. Semantic communication codes source data so that extracting main semantics from received messages can be easy by separating unwanted data using powerful interpreters. Moreover, high amount of bit errors and narrow bandwidth issues can be handled through this process. [219] applied the generic model of semantic communication (GMSC) in order to propose a lossless semantic data compression algorithm by significant reduction of the conveyed message size at semantic level. Avoiding the traditional symbols/bits, communication spectrum can be utilized efficiently by enabling semantic data transfer from the devices to the server. Researchers investigated smart semantic communication from the viewpoint of the connection layer, however, internet and physical layers should be studied further to address the issues regarding spectrum distribution within a heterogeneous semantic network [220-221]. As several devices provide necessary data for the training of the semantic communication framework, the cost of communication becomes higher. Depending on the sender categories, recovering the transmitted data at receiver end is the primary intention of joint source-channel coding for images and texts [222]. For instance of application of ML tools to the physical layer of a semantic communication systems have been already studied, under unknown channels, using a CNN [221], a RNN [223], and a DNN [224] becoming gradually insufficient to process diversified service requirements under various application scenarios which unable to perform properly for recovering the source information, because the kernel size in CNN is small to guarantee the computational efficiency and RNNs are time-consuming. [223]. That is why, FL enabled semantic communication can facilitate designing channel decoder and encoder for establishing suitable UE-BS connections which uses non-IID and unbalanced, massively distributed data over limited communication resources resulting improves the accuracy of source information recovery. Managing network resources is highly complex due to the network demands, channel requirements, bandwidth shortage, high power consumption, and memory limitations for intelligent semantic communication. Therefore, FL enhanced RIS-assisted semantic communication systems facilitates optimizing and controlling the reconfigurable components and also the panels with a limited number of pilots or CSI is required for training the transceiver. It enables the fast training of the network which maximizes the capacity and minimizes the semantic errors.

VIII. Conclusions

This paper has studied the modern research contributions regarding future intelligent IoT networks that considered the RIS functionality policies, possible utilization scopes and associated practical challenges, combined passive beamforming design-based resource distribution and RIS incorporated with other crucial future technologies like backscatter communications, THz communications, optical communications, SWIPT, UAV, CR, PLS and STAR-RIS. Moreover, this paper has discussed RIS-based ML-enabled IoT networks for random variations of propagation channels and mobility of UEs. We presented the conventional approaches for resource management, including their disadvantages and limitations. Furthermore, we have illustrated how the emerging DL approaches can overcome these shortcomings to enable ML-based resource management. Lastly, some possible barriers and further research scopes were mentioned for applying RIS in next generation IoT networks.

REFERENCES

[1] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M. -S. Alouini and R. Zhang, "Wireless Communications Through Reconfigurable Intelligent Surfaces," *IEEE Access*, vol. 7, pp. 116753-116773, 2019.

[2] Q. Wu and R. Zhang, "Towards Smart and Reconfigurable Environment: Intelligent reflecting surface vs. decode-and-forward: How large surfaces are needed to beat relaying Surface Aided Wireless Network," *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106-112, January 2020.

[3] C. Wu, Y. Liu, X. Mu, X. Gu and O. A. Dobre, "Coverage Characterization of STAR-RIS Networks: NOMA and OMA," *IEEE Commun. Lett.*, 2021.

[4] M. A. ElMossallamy, H. Zhang, L. Song, K. G. Seddik, Z. Han and G. Y. Li, "Reconfigurable Intelligent Surfaces for Wireless Communications: Principles, Challenges, and Opportunities," *IEEE Trans. on Cogn. Commun. and Netw.*, vol. 6, no. 3, pp. 990-1002, Sept. 2020.

[5] J. Wang, W. Tang, Y. Han, S. Jin, X. Li, C. K. Wen, Q. Cheng and T. J. Cui, "Interplay between RIS and AI in Wireless Communications: Fundamentals, Architectures, Applications, and Open Research Problems," *IEEE J. on Sel. Areas in Commun.*, 2021.

[6] M. Di Renzo, K. Ntontin, J. Song, F. H. Danufane, X. Qian, F. Lazarakis, J. de Rosny, D. . Phan-Huy, O. Simeone, R. Zhang, M. Debbah, G. Lerosey, M. Fink, S. Tretyakov and S. Shamai, "Reconfigurable intelligent surfaces vs. relaying: Differences, similarities, and performance comparison," *IEEE Open J. of the Commun. Soc.*, vol. 1, pp. 798–807, 2020.

[7] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming," *IEEE Trans. on Wireless Commun.*, vol. 18, no. 11, pp. 5394–5409, Nov. 2019.

[8] B. Sheen, J. Yang, X. Feng and M. M. U. Chowdhury, "A Deep Learning Based Modeling of Reconfigurable Intelligent Surface Assisted Wireless Communications for Phase Shift Configuration," *IEEE Open J. of the Commun. Soc.*, vol. 2, pp. 262-272, 2021.

[9] C. D. Alwis et al., "Survey on 6G Frontiers: Trends, Applications, Requirements, Technologies and Future Research," *IEEE Open J. of the Commun. Soc.*, vol. 2, pp. 836-886, 2021.

[10] R. Alghamdi, R. Alhadrami, D. Alhothali, H. Almorad, A. Faisal, S. Helal, R. Shalabi, R. Asfour, N. Hammad and A. Shams, "Intelligent Surfaces for 6G Wireless Networks: A Survey of Optimization and Performance Analysis Techniques," *IEEE Access*, vol. 8, pp. 202795-202818, 2020.

[11] G. C. Alexandropoulos, G. Lerosey, M. Debbah and M. Fink, "Reconfigurable intelligent surfaces and metamaterials: The potential of wave propagation control for 6G wireless communications," *IEEE ComSoc TCCN Newsletter*, vol. 6, no. 1, June 2020.

[12] K. Yang, Y. Shi, Y. Zhou, Z. Yang, L. Fu and W. Chen, "Federated Machine Learning for Intelligent IoT via Reconfigurable Intelligent Surface," *IEEE Netw.*, vol. 34, no. 5, pp. 16-22, Oct. 2020.

[13] Y. Liu, X. Liu, X. Mu, T. Hou, J. Xu, M. Di Renzo and N. Al-Dhahir, "Reconfigurable Intelligent Surfaces: Principles and Opportunities," *IEEE Commun. Surv. & Tut.*, 2021.

[14] L. Mohjazi, A. Zoha, L. Bariah, S. Muhaidat, P. C. Sofotasios, M. A. Imran and O. A. Dobre, "An Outlook on the Interplay of Artificial Intelligence and Software-Defined Metasurfaces: An Overview of Opportunities and Limitations," *IEEE Veh. Technol. Mag.*, vol. 15, no. 4, pp. 62-73, Dec. 2020.

[15] C. Huang, R. Mo and C. Yuen, "Reconfigurable Intelligent Surface Assisted Multiuser MISO Systems Exploiting Deep Reinforcement Learning," *IEEE J. on Sel. Areas in Commun.*, vol. 38, no. 8, pp. 1839-1850, Aug. 2020.

[16] Z. T. Azim, S. A. Shaon, S. K. Das and M. G. Mostafa, "Optimization of Reconfigurable Intelligent Surface for M2M Communications over Cellular Networks," *in 2021 5th Int. Conf. on Elect. Eng. and Inf. Commun. Technol. (ICEEICT)*, 2021, pp. 1-7.

[17] Y.-C. Liang, R. Long, Q. Zhang, J. Chen, H. V. Cheng and H. Guo, "Large intelligent surface/antennas (LISA): Making reflective radios smart," *J. of Commun. and Inf. Netw.*, vol. 4, no. 2, pp. 40–50, 2019.

[18] M. Di Renzo, A. Zappone, M. Debbah, M. S. Alouini, C. Yuen, J. de Rosny and S. Tretyakov, "Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and the road ahead," *IEEE J. on Sel. Areas Commun.*, vol. 38, no. 11, pp. 2450–2525, 2020.

[19] C. Huang, S. Hu, G. C. Alexandropoulos, A. Zappone, C. Yuen, R. Zhang, M. D. Renzo and M. Debbah, "Holographic MIMO surfaces for 6G wireless networks: Opportunities, challenges, and trends," *IEEE Wireless Commun.*, vol. 27, no. 5, pp. 118–125, 2020.

[20] H. Gacanin and M. Di Renzo, "Wireless 2.0: Toward an intelligent radio environment empowered by reconfigurable meta-surfaces and artificial intelligence," *IEEE Veh. Technol. Mag.*, vol. 15, no. 4, pp. 74–82, 2020.

[21] M. Di Renzo, M. Debbah, D.-T. Phan-Huy, A. Zappone, M.-S. Alouini, C. Yuen, V. Sciancalepore, G. C. Alexandropoulos, J. Hoydis, H. Gacanin, J. de Rosny, A. Bounceur, G. Lerosey and M. Fink, "Smart radio environments empowered by AI reconfigurable meta-surfaces: An idea whose time has come," *EURASIP J. on Wireless Commun.*, 2019.

[22] S. Gong, X. Lu, D. T. Hoang, D. Niyato, L. Shu, D. I. Kim and Y. C. Liang, "Towards smart wireless communications via intelligent reflecting surfaces: A contemporary survey," *IEEE Commun. Surv. & Tut.*, vol. 22, no. 4, pp. 2283–2314, 2020.

[23] Q. Wu, S. Zhang, B. Zheng, C. You and R. Zhang, "Intelligent reflecting surface aided wireless communications: A tutorial," *IEEE Trans. on Commun.*, 2021.

[24] Q. Wu and R. Zhang, "Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network," *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106–112, 2020.

[25] C. Liaskos, S. Nie, A. Tsioliaridou, A. Pitsillides, S. Ioannidis and I. Akyildiz, "A New Wireless Communication Paradigm through Software-Controlled Metasurfaces," *IEEE Commun. Mag.*, vol. 56, no. 9, pp. 162-169, Sept. 2018.

[26] L. Subrt and P. Pechac, "Intelligent walls as autonomous parts of smart indoor environments," *IET Commun.*, vol. 6, no. 8, pp. 1004–1010, May 2012.

[27] S. Hu, F. Rusek and O. Edfors, "Beyond massive MIMO: The potential of positioning with large intelligent surfaces," *IEEE Trans. on Signal Process.*, vol. 66, no. 7, pp. 1761–1774, Apr. 2018.

[28] X. Tan, Z. Sun, D. Koutsonikolas and J. M. Jornet, "Enabling indoor mobile millimeter-wave networks based on smart reflect-arrays," *in Proc. IEEE INFOCOM*, Apr. 2018, pp. 270–278.

[29] C. Liaskos, S. Nie, A. Tsioliaridou, A. Pitsillides, S. Ioannidis and I. Akyildiz, "A novel communication paradigm for high capacity and security via programmable indoor wireless environments in next generation wireless systems," *Ad Hoc Netw.*, vol. 87, pp. 1–16, May 2019.

[30] G. Yang, X. Xu and Y.-C. Liang, "Intelligent reflecting surface assisted non-orthogonal multiple access," arXiv: 1907.03133, 2019.

[31] E. Basar, "Reconfigurable intelligent surface-based index modulation: A new beyond MIMO paradigm for 6G," *IEEE Trans. on Commun.*, vol. 68, no. 5, pp. 3187–3196, May 2020.

[32] M. Jung, W. Saad, Y. Jang, G. Kong and S. Choi, "Performance analysis of large intelligent surfaces (LISs): Asymptotic data rate and channel hardening effects," *IEEE Trans. on Wireless Commun.*, vol. 19, no. 3, pp. 2052–2065, Mar. 2020.

[33] S. Zhou, W. Xu, K. Wang, M. Di Renzo, and M.-S. Alouini, "Spectral and energy efficiency of IRS-assisted MISO communication with hardware impairments," *IEEE Wireless Commun. Lett.*, vol. 9, no. 9, pp. 1366–1369, 2020.

[34] Q. Wu and R. Zhang, "Beamforming optimization for wireless network aided by intelligent reflecting surface with discrete phase shifts," *IEEE Trans. on Commun.*, vol. 68, no. 3, pp. 1838–1851, 2020.

[35] J. Zhu, Y. Huang, J. Wang, K. Navaie and Z. Ding, "Power efficient IRS-assisted NOMA," *IEEE Trans. on Commun.*, vol. 69, no. 2, pp. 900–913, 2021.

[36] N. Kaina, M. Dupre, G. Lerosey and M. Fink, "Shaping complex microwave fields in reverberating media with binary tunable metasurfaces," *Sci. Rep.*, vol. 4, no. 1, Oct. 2014, Art. no. 6693.

[37] H. Yang, X. Cao, F. Yang, J. Gao, S. Xu, M. Li, X. Chen, Y. Zhao, Y. Zheng and S. Li, "A programmable metasurface with dynamic polarization, scattering and focusing control," *Sci. Rep.*, vol. 6, Oct. 2016, Art. no. 35692.

[38] L. Zhang, X. Q. Chen, S. Liu, Q. Zhang, J. Zhao, J. Y. Dai, G. D. Bai, X. Wan, Q. Cheng, G. Castaldi, V. Galdi and T. J. Cui, "Space-time-coding digital metasurfaces," *Nature Commun.*, vol. 9, Oct. 2018, Art. no. 4334.

[39] A. Taha, M. Alrabeiah and A. Alkhateeb, "Deep Learning for Large Intelligent Surfaces in Millimeter Wave and Massive MIMO Systems," *in Proc. IEEE GLOBECOM*, 2019, pp. 1-6.

[40] Ö. Özdoğan and E. Björnson, "Deep Learning-based Phase Reconfiguration for Intelligent Reflecting Surfaces," *54th Asilomar Conf. on Signals, Syst., and Comput.*, 2020, pp. 707-711.

[41] T. Jiang, H. V. Cheng and W. Yu, "Learning to Beamform for Intelligent Reflecting Surface with Implicit Channel Estimate," *in Proc. IEEE GLOBECOM*, 2020, pp. 1-6.

[42] C. Huang, G. C. Alexandropoulos, C. Yuen and M. Debbah, "Indoor signal focusing with deep learning designed reconfigurable intelligent surfaces," *in Proc. IEEE 20th Int. Workshop on Signal Process. Adv. in Wireless Commun. (SPAWC)*, Jul. 2019, pp. 1–5.

[43] J. Gao, C. Zhong, X. Chen, H. Lin and Z. Zhang, "Unsupervised learning for passive beamforming," *IEEE Commun. Lett.*, vol. 24, no. 5, pp. 1052–1056, May 2020.

[44] M. Chen, U. Challita, W. Saad, C. Yin and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: A tutorial," *IEEE Commun. Surveys & Tut.*, vol. 21, no. 4, pp. 3039–3071, 4th Quart., 2019.

[45] A. Taha, Y. Zhang, F. B. Mismar and A. Alkhateeb, "Deep reinforcement learning for intelligent reflecting surfaces: Towards standalone operation," *in Proc. IEEE 21st Int. Workshop on Signal Process. Adv. in Wireless Commun. (SPAWC)*, May 2020, pp. 1–5.

[46] G. Lee, M. Jung, A. T. Z. Kasgari, W. Saad, and M. Bennis, "Deep reinforcement learning for energy-efficient networking with reconfigurable intelligent surfaces," *in Proc. IEEE ICC*, Jun. 2020, pp. 1–6.

[47] A. M. Elbir and S. Coleri, "Federated Learning for Channel Estimation in Conventional and IRS-Assisted Massive MIMO," *arXiv preprint* arXiv: 2008.10846, 2020.

[48] D. Ma et al., "Distributed Rate Optimization for Intelligent Reflecting Surface with Federated Learning," *2020 ICC Workshops*, pp. 1–6, Jul 2020.

[49] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu and N. D. Sidiropoulos, "Learning to optimize: Training deep neural networks for interference management," *IEEE Trans. on Signal Process.*, vol. 66, no. 20, pp. 5438–5453, 2018.

[50] C. Zhang, P. Patras and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Commun. Surv. & Tut.*, vol. 21, no. 3, pp. 2224–2287, 3rd Quart. 2019.

[51] D. R. Smith, O. Yurduseven, L. P. Mancera, P. Bowen and N. B. Kundtz, "Analysis of a waveguide-fed metasurfaces antenna," *Physical Rev. Applied*, vol. 8, no. 5, p. 054048, 2017.

[52] B. O. Zhu, K. Chen, N. Jia, L. Sun, J. Zhao, T. Jiang and Y. Feng, "Dynamic control of electromagnetic wave propagation with the equivalent principle inspired tunable metasurface," *Scientific reports*, vol. 4, no. 1, pp. 1–7, 2014.

[53] J. Y. Dai, J. Zhao, Q. Cheng and T. J. Cui, "Independent control of harmonic amplitudes and phases via a time-domain digital coding metasurface," *Light: Sci. & Appl.*, vol. 7, no. 1, p. 90, 2018.

[54] S. R. Rengarajan and Y. Rahmat-Samii, "The field equivalence principle: illustration of the establishment of the non-intuitive null fields," *IEEE Antennas and Propag. Mag.*, vol. 42, no. 4, pp. 122-128, Aug. 2000.

[55] V. S. Asadchy, M. Albooyeh, S. N. Tcvetkova, A. Díaz-Rubio, Y. Ra'di and S. Tretyakov, "Perfect control of reflection and refraction using spatially dispersive metasurfaces," *Physical Rev. B*, vol. 94, no. 7, p. 075142, 2016.

[56] R. J. Bell, K. R. Armstrong, C. S. Nichols and R. W. Bradley, "Generalized laws of refraction and reflection," *JOSA, vol.* 59, no. 2, pp. 187–189, 1969.

[57] J. Huang and J. A. Encinar, "Reflectarray antennas, a john wiley sons," *Inc., Publication*, 2008.

[58] M. Fadil H. Danufaneand Di Renzo, J. de Rosny and S. Tretyakov, "On the path-loss of reconfigurable intelligent surfaces: An approach based on green's theorem applied to vector fields," arXiv:2007.13158, 2020.

[59] E. Basar and H. V. Poor, "Present and Future of Reconfigurable Intelligent Surface-Empowered Communications," arXiv: 2105.00671, 2021.

[60] I. M. Vellekoop and A. P. Mosk, "Phase control algorithms for focusing light through turbid media," *Optics Commun.*, vol. 281, no. 11, pp. 3071–3080, 2008.

[61] S. Basharat, S. A. Hassan, A. Mahmood, Z. Ding and M. Gidlund, "Reconfigurable Intelligent Surface Assisted Backscatter Communication: A New Frontier for Enabling 6G IoT Networks," https://arxiv.org/abs/2107.07813, 2021.

[62] M. A. Sedaghat, V. I. Barousis, R. R. Müller and C. B. Papadias, "Load modulated arrays: A low-complexity antenna," *IEEE Commun. Mag.*, vol. 54, no. 3, pp. 46–52, Mar. 2016.

[63] A. F. Molisch, V. V. Ratnam, S. Han, Z. Li, S. L. H. Nguyen, L. Li and K. Haneda, "Hybrid beamforming for massive MIMO: A survey," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 134–141, Sep. 2017.

[64] E. Vlachos, G. C. Alexandropoulos and J. Thompson, "Wideband MIMO channel estimation for hybrid beamforming millimeter wave systems via random spatial sampling," *IEEE J. on Sel. Topics Signal Process.*, vol. 13, no. 5, pp. 1136–1150, Sep. 2019.

[65] H. Ye, G. Y. Li and B. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114–117, 2018.

[66] M. Fu, Y. Zhou and Y. Shi, "Reconfigurable intelligent surface empowered downlink non-orthogonal multiple access," *IEEE Trans. on Commun.*, 2021.

[67] M. Di Renzo, M. Debbah, D.-T. Phan-Huy, A. Zappone, M.-S. Alouini, C. Yuen, V. Sciancalepore, G. C. Alexandropoulos, J. Hoydis, H. Gacanin, J. de Rosny, A. Bounceur, G. Lerosey and M. Fink, "Smart radio environments empowered by reconfigurable AI meta-surfaces: An idea whose time has come," *EURASIP J. on Wireless Commun. Netw.*, vol. 2019, p. 129, May 2019.

[68] O. Tsilipakos, A. C. Tasolamprou, A. Pitilakis, F. Liu, X. Wang, M. S. Mirmoosa, D. C. Tzarouchis, S. Abadal, H. Taghvaee, C. Liaskos, A. Tsioliaridou, J. Georgiou, A. C. Aparicio, E. Alarcón, S. Ioannidis, A. Pitsillides, I. F. Akyildiz, N. V. Kantartzis, E. N. Economou, C. M. Soukoulis, M. Kafesaki and S. Tretyakov, "Toward Intelligent Metasurfaces: The Progress from Globally Tunable Metasurfaces to Software-Defined Metasurfaces with an Embedded Network of Controllers," *in Advanced Optical Materials*, vol. 8, issue 17, Sep. 2020.

[69] T. Rappaport, Wireless Communications: Principles and Practice, 2nd ed. *Upper Saddle River, NJ: Prentice Hall PTR*, 2001.

[70] T. Rappaport and S. Sandhu, "Radio-wave propagation for emerging wireless personal-communication systems," *IEEE Antennas Propag. & Mag.*, vol. 36, no. 5, pp. 14–24, Oct. 1994.

[71] K. R. Schaubach, N. J. Davis and T. S. Rappaport, "A ray tracing method for predicting path loss and delay spread in microcellular environments," *in Proc. 42nd VTS Conf.-Frontiers of Technol.* 1992, pp. 932–935.

[72] E. Ben-Dor, T. S. Rappaport, Y. Qiao and S. J. Lauffenburger, "Millimeter-wave 60 GHz outdoor and vehicle AOA propagation measurements using a broadband channel sounder," *in Proc. IEEE GLOBECOM*, Houston, TX, Dec. 2011.

[73] A. Díaz-Rubio, V. S. Asadchy, A. Elsakka and S. A. Tretyakov, "From the generalized reflection law to the realization of perfect anomalous reflectors," *Sci. Adv.*, vol. 3, no. 8, Aug. 2017.

[74] W. Tang, M. Z. Chen, X. Chen, J. Y. Dai, Y. Han, M. Di Renzo, Y. Zeng, S. Jin, Q. Cheng and T. J. Cui, "Wireless communications with reconfigurable intelligent surface: Path loss modeling and experimental measurement," *IEEE Trans. on Wireless Commun.*, vol. 20, no. 1, pp. 421–439, 2021.

[75] A. U. Makarfi, K. M. Rabie, O. Kaiwartya, O. S. Badarneh, X. Li and R. Kharel, "Reconfigurable intelligent surface enabled iot networks in generalized fading channels," *in Proc. IEEE ICC*, 2020, pp. 1–6.

[76] Y. Cheng, K. H. Li, Y. Liu, K. C. Teh and G. K. Karagiannidis, "Non-orthogonal multiple access (NOMA) with multiple intelligent reflecting surfaces," arXiv:2011.00211, 2020.

[77] J. Xu and Y. Liu, "A novel physics-based channel model for reconfigurable intelligent surface-assisted multi-user communication systems," arXiv:2008.00619, 2020.

[78] Z. Zhang, Y. Cui, F. Yang and L. Ding, "Analysis and optimization of outage probability in multi-intelligent reflecting surface-assisted systems," arXiv:1909.02193, 2019.

[79] A. A. A. Boulogeorgos and A. Alexiou, "Ergodic capacity analysis of reconfigurable intelligent surface assisted wireless systems," *in Proc. IEEE 3rd 5GWF*, 2020, pp. 395–400.

[80] T. Hou, Y. Liu, Z. Song, X. Sun and Y. Chen, “MIMO-NOMA networks relying on reconfigurable intelligent surface: A signal cancellation-based design,” *IEEE Trans. on Commun.*, vol. 68, no. 11, pp. 6932–6944, 2020.

[81] K. Ntontin, J. Song and M. Di Renzo, “Multi-antenna relaying and reconfigurable intelligent surfaces: End-to-end SNR and achievable rate,” arXiv:1908.07967, 2019.

[82] D. Lin, M. Melli, E. Poliakov et al., ”Optical metasurfaces for high angle steering at visible wavelengths,” *Sci. Rep.* 7, article no. 2286, 2017.

[83] S. Abadal, C. Liaskos, A. Tsioliaridou, S. Ioannidis, A. Pitsillides, J. Solé-Pareta, E. Alarcón and A. Cabellos-Aparicio, “Computing and communications for the software-defined metamaterial paradigm: A context analysis,” *IEEE access*, vol. 5, pp. 6225–6235, 2017.

[84] X. Tan, Z. Sun, J. M. Jornet and D. Pados, “Increasing indoor spectrum sharing capacity using smart reflect-array,” *in Proc. IEEE ICC*, 2016.

[85] L. Zhang, X. Q. Chen, S. Liu, Q. Zhang, J. Zhao, J. Y. Dai, G. D. Bai, X. Wan, Q. Cheng and T. J. Cui, “Space-timecoding digital metasurfaces,” *Nature commun.*, vol. 9, no. 1, p. 4334, 2018.

[86] W. Tang, X. Li, J. Y. Dai, S. Jin, Y. Zeng, Q. Cheng and T. J. Cui, ”Wireless communications with programmable metasurface: Transceiver design and experimental results,” *China Commun.*, vol. 16, no. 5, pp. 46–61, May 2019.

[87] H. Lu, Y. Zeng, S. Jin and R. Zhang, “Enabling panoramic full-angle reflection via aerial intelligent reflecting surface,” *in Proc. IEEE ICC*, 2020, pp. 1–6.

[88] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah and C. Yuen, “Reconfigurable intelligent surfaces for energy efficiency in wireless communication,” *IEEE Trans. on Wireless Commun.*, vol. 18, no. 8, pp. 4157–4170, 2019.

[89] H. Guo, Y.-C. Liang, J. Chen and E. G. Larsson, “Weighted sum-rate optimization for intelligent reflecting surface enhanced wireless networks,” arXiv:1905.07920, 2019.

[90] H. Shen, W. Xu, S. Gong, Z. He and C. Zhao, “Secrecy rate maximization for intelligent reflecting surface assisted multi-antenna communications,” *IEEE Commun. Lett.*, vol. 23, no. 9, pp. 1488–1492, 2019.

[91] E. Basar and I. Yildirim, “SimRIS channel simulator for reconfigurable intelligent surface-empowered communication systems,” May 2020. Accessed: Aug. 12, 2020. [Online]. Available: http://arxiv.org/abs/2006.00468.

[92] X. Liu, Y. Liu, Y. Chen and L. Hanzo, “Trajectory design and power control for multi-UAV assisted wireless networks: A machine learning approach,” *IEEE Trans. on Veh. Technol.*, vol. 68, no. 8, pp. 7957–7969, 2019.

[93] Q. Zhang, W. Saad and M. Bennis, “Millimeter wave communications with an intelligent reflector: Performance optimization and distributional reinforcement learning,” arXiv:2002.10572, 2020.

[94] C. Pan, H. Ren, K. Wang, W. Xu, M. Elkashlan, A. Nallanathan and L. Hanzo, “Multicell MIMO communications relying on intelligent reflecting surfaces,” *IEEE Trans. on Wireless Commun.*, vol. 19, no. 8, pp. 5218–5233, 2020.

[95] Q. U. A. Nadeem, A. Kammoun, A. Chaaban, M. Debbah and M. S. Alouini, “Asymptotic max-min SINR analysis of reconfigurable intelligent surface assisted MISO systems,” *IEEE Trans. on Wireless Commun.*, vol. 19, no. 12, pp. 7748–7764, 2020.

[96] J. Ye, S. Guo and M. S. Alouini, “Joint reflecting and precoding designs for SER minimization in reconfigurable intelligent surfaces assisted MIMO systems,” *IEEE Trans. on Wireless Commun.*, vol. 19, no. 8, pp. 5561–5574, 2020.

[97] K. Umebayashi, M. Kobayashi and M. Lopez-Benıtez, “Efficient time domain deterministic-stochastic model of spectrum usage,” *IEEE Trans. on Wireless Commun.*, vol. 17, no. 3, pp. 1518–1527, 2017.

[98] Z. Feng, X. Li, Q. Zhang and W. Li, “Proactive radio resource optimization with margin prediction: A data mining approach,” *IEEE Trans. on Veh. Technol.*, vol. 66, no. 10, pp. 9050–9060, 2017.

[99] K. G. M. Thilina, E. Hossain and D. I. Kim, “DCCC-MAC: A dynamic common-control-channel-based MAC protocol for cellular cognitive radio networks,” *IEEE Trans. on Veh. Technol.*, vol. 65, no. 5, pp. 3597–3613, 2015.

[100] P. Abouzar, K. Shafiee, D. G. Michelson and V. C. Leung, “Action-based scheduling technique for 802.15. 4/zigbee wireless body area networks,” *in Proc. IEEE PIMRC*, 2011, pp. 2188–2192.

[101] J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen and L. Hanzo, “Thirty years of machine learning: the road to paretooptimal wireless networks,” *IEEE Commun. Surv. & Tut.*, vol. 22, no. 3, pp. 1472–1514, 2020.

[102] X. Liu, Y. Liu and Y. Chen, “Reinforcement learning in multiple-UAV networks: Deployment and movement design,” *IEEE Trans. on Veh. Technol.*, vol. 68, no. 8, pp. 8036–8049, 2019.

[103] A. Assra, J. Yang and B. Champagne, “An EM approach for cooperative spectrum sensing in multiantenna CR networks,” *IEEE Trans. on Veh. Technol.*, vol. 65, no. 3, pp. 1229–1243, 2015.

[104] A. Morell, A. Correa, M. Barcelo and J. L. Vicario, “Data aggregation and principal component analysis in WSNs,” *IEEE Trans. on Wireless Commun.*, vol. 15, no. 6, pp. 3908–3919, 2016.

[105] J. Li, H. Zhang and M. Fan, “Digital self-interference cancellation based on independent component analysis for co-time co-frequency full-duplex communication systems,” *IEEE Access*, vol. 5, pp. 10 222–10 231, 201.

[106] W. Ni, Y. Liu, Z. Yang, H. Tian and X. Shen, “Federated Learning in Multi-RIS Aided Systems,” https://arxiv.org/abs/2010.13333v2, 2021.

[107] P. D. Diamantoulakis, V. M. Kapinas and G. K. Karagiannidis, “Big data analytics for dynamic energy management in smart grids,” *Big Data Research*, vol. 2, no. 3, pp. 94–101, 2015.

[108] Y. Wang, I. L. Bennani, X. Liu, M. Sun and Y. Zhou, “Electricity consumer characteristics identification: A federated learning approach,” *IEEE Trans. on Smart Grid*, pp. 1–1, 2021.

[109] S. Zhai, X. Jin, L. Wei, H. Luo and M. Cao, “Dynamic federated learning for GMEC with time-varying wireless link,” *IEEE Access*, vol. 9, pp. 10 400–10 412, 2021.

[110] Y. M. Saputra, D. T. Hoang, D. N. Nguyen, E. Dutkiewicz, M. D. Mueck and S. Srikanteswara, “Energy demand prediction with federated learning for electric vehicle networks,” *in Proc. IEEE GLOBECOM*, 2019, pp. 1–6.

[111] Z. Du, C. Wu, T. Yoshinaga, K.-L. A. Yau, Y. Ji and J. Li, “Federated learning for vehicular internet of things: Recent advances and open issues,” *IEEE Open J. of the Comput. Soc.*, vol. 1, pp. 45–61, 2020.

[112] D. Schmalstieg and T. Höllerer, “Augmented reality: Principles and practice,” *2017 IEEE Virtual Reality (VR)*, 2017, pp. 425-426.

[113] D. Chen, L. J. Xie, B. Kim, L. Wang, C. S. Hong, L.-C. Wang and Z. Han, “Federated learning based mobile edge computing for augmented reality applications,” *in Proc. IEEE ICNC*, 2020, pp. 767–773.

[114] R. Zhong, X. Liu, Y. Liu, Y. Chen and Z. Han, “Mobile Reconfigurable Intelligent Surfaces for NOMA Networks: Federated Learning Approaches,” March 2021, arXiv: 2105.09462. [Online]. Available: https://arxiv.org/abs/2105.09462.

[115] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver and D. Wierstra, “Continuous control with deep reinforcement learning,” *arXiv preprint arXiv:1509.02971*, 2015.

[116] S. K. Das and M. F. Hossain, “A Location-Aware Power Control Mechanism for Interference Mitigation in M2M Communications over Cellular Networks,” *Comput. & Elect. Eng.*, vol. 88, pp. 1–23, Dec. 2020.

[117] A. M. Elbir, A. Papazafeiropoulos, P. Kourtessis and S. Chatzinotas, “Deep channel learning for large intelligent surfaces aided mm-Wave massive MIMO systems,” *IEEE Wireless Commun. Lett.*, vol. 9, no. 9, pp. 1447–1451, 2020.

[118] S. Liu, Z. Gao, J. Zhang, M. Di Renzo and M.-S. Alouini, “Deep denoising neural network assisted compressive channel estimation for mmWave intelligent reflecting surfaces,” *arXiv preprint arXiv:2006.02201*, 2020.

[119] F. Jiang, L. Yang, D. B. da Costa and Q. Wu, “Channel estimation via direct calculation and deep learning for RIS-aided mmwave systems,” *arXiv preprint arXiv: 2008.04704*, 2020.

[120] C. Liu, X. Liu, D. W. K. Ng and J. Yuan, “Deep residual learning for channel estimation in intelligent reflecting surface-assisted multi-user communications,” *arXiv preprint arXiv: 2009.01423*, 2020.

[121] S. Hashima, K. Hatano and E. M. Mohamed, “Multiagent Multi-Armed Bandit Schemes for Gateway Selection in UAV Networks,” *IEEE Globecom Workshops*, 2020, pp. 1-6.

[122] A. G. Sreedevi and T. Rama Rao, “Reinforcement learning algorithm for 5G indoor Device-to-Device communications,” *Trans. on Emerg. Telecommun. Technol.*, vol. 30, issue 9, 2019.

[123] A. Ortiz, A. Asadi, M. Engelhardt, A. Klein and M. Hollick, “CBMoS: Combinatorial Bandit Learning for Mode Selection and Resource Allocation in D2D Systems,” *IEEE J. on Sel. Areas in Commun.*, vol. 37, no. 10, pp. 2225-2238, Oct. 2019.

[124] A. B. Zaky, J. Z. Huang, K. Wu and B. M. ElHalawany, “Generative neural network based spectrum sharing using linear sum assignment problems,” *China Commun.*, vol. 17, no. 2, pp. 14-29, Feb. 2020.

[125] T. W. Ban and W. Lee, "A Deep Learning Based Transmission Algorithm for Mobile Device-to-Device Networks," *Electron.* 2019, 8, 1361.

[126] X. Huang, M. Zeng, J. Fan, X. Fan and X. Tang, "A Full Duplex D2D Clustering Resource Allocation Scheme Based on a K-Means Algorithm,"*Wireless Commun. & Mobile Comput.*, pp. 1–8, 2018.

[127] Y. Long, R. Yamamoto, T. Yamazaki and Y. Tanaka, "A Deep Learning Based Social-aware D2D Peer Discovery Mechanism,"*in Proc. ICACT*, 2019, pp. 91-97.

[128] S. Hashima, K. Hatano, E. Takimoto and E. Mahmoud Mohamed, "Neighbor Discovery and Selection in Millimeter Wave D2D Networks Using Stochastic MAB," *IEEE Commun. Lett.*, vol. 24, no. 8, pp. 1840-1844, Aug. 2020.

[129] S. Hashima, K. Hatano, E. Takimoto and E. M. Mohamed, "Minimax Optimal Stochastic Strategy (MOSS) For Neighbor Discovery and Selection In Millimeter Wave D2D Networks," *in Proc. WPMC*, 2020, pp. 1-6.

[130] Z. Fan, X. Gu, S. Nie and M. Chen, "D2D power control based on supervised and unsupervised learning," *in Proc. IEEE ICCC*, 2017, pp. 558-563.

[131] M. Najla, D. Gesbert, Z. Becvar and P. Mach, "Machine Learning for Power Control in D2D Communication Based on Cellular Channel Gains," *IEEE Globecom Workshops*, 2019, pp. 1-6.

[132] J. Kim, J. Park, J. Noh and S. Cho, "Autonomous Power Allocation Based on Distributed Deep Learning for Device-to-Device Communication Underlaying Cellular Network," *IEEE Access*, vol. 8, pp. 107853-107864, 2020.

[133] M. K. Sharma, A. Zappone, M. Debbah and M. Assaad, "Multi -Agent Deep Reinforcement Learning based Power Control for Large Energy Harvesting Networks," *in Proc. WiOPT*, 2019, pp. 1-7.

[134] W. Jiang, G. Feng, S. Qin, T. S. P. Yum and G. Cao, "Multi-Agent Reinforcement Learning for Efficient Content Caching in Mobile D2D Networks," *IEEE Trans. on Wireless Commun.*, vol. 18, no. 3, pp. 1610-1622, March 2019.

[135] Z. Zhang, X. Guo and Y. Lin, "Trust Management Method of D2D Communication Based on RF Fingerprint Identification," *IEEE Access*, vol. 6, pp. 66082-66087, 2018.

[136] X. Yu, D. Xu and R. Schober, "Enabling secure wireless communications via intelligent reflecting surfaces," *in Proc. IEEE GLOBECOM*, 2019, pp. 1–6.

[137] M. Cui, G. Zhang and R. Zhang, "Secure wireless communication via intelligent reflecting surface," *IEEE Wireless Commun. Lett.*, vol. 8, no. 5, pp. 1410–1414, 2019.

[138] Z. Chu, W. Hao, P. Xiao and J. Shi, "Intelligent reflecting surface aided multi-antenna secure transmission," *IEEE Wireless Commun. Lett.*, vol. 9, no. 1, pp. 108–112, 2020.

[139] L. Dong and H. Wang, "Secure MIMO transmission via intelligent reflecting surface," *IEEE Wireless Commun. Lett.*, vol. 9, no. 6, pp. 787–790, 2020.

[140] W. Jiang, Y. Zhang, J. Wu, W. Feng and Y. Jin, "Intelligent Reflecting Surface Assisted Secure Wireless Communications with Multiple-Transmit and Multiple-Receive Antennas," *IEEE Access*, vol. 8, pp. 86659-86673, 2020.

[141] S. Mao et al., "Reconfigurable Intelligent Surface-Assisted Secure Mobile Edge Computing Networks," *IEEE Trans. on Veh. Technol.*, vol. 71, no. 6, pp. 6647-6660, June 2022.

[142] J. Chen, Y. Liang, Y. Pei and H. Guo, "Intelligent reflecting surface: A programmable wireless environment for physical layer security," *IEEE Access*, vol. 7, pp. 82 599–82 612, 2019.

[143] X. Guan, Q. Wu and R. Zhang, "Intelligent reflecting surface assisted secrecy communication: Is artificial noise helpful or not?" *IEEE Wireless Commun. Lett.*, vol. 9, no. 6, pp. 778–782, 2020.

[144] S. Li, B. Duo, X. Yuan, Y.-C. Liang and M. Di Renzo, "Reconfigurable intelligent surface assisted UAV communication: Joint trajectory design and passive beamforming," *IEEE Wireless Commun. Lett.*, vol. 9, no. 5, pp. 716–720, 2020.

[145] Q. Wang, Z. Chen, H. Li and S. Li, "Joint power and trajectory design for physical-layer secrecy in the UAV-aided mobile relaying system," *IEEE Access*, vol. 6, pp. 62 849–62 855, 2018.

[146] A. Osseiran, F. Boccardi, V. Braun, Kusume et al., "Scenarios for 5G mobile and wireless communications: the vision of the METIS project," *IEEE Commun. Mag.*, vol. 52, no. 5, pp. 26–35, 2014.

[147] L. Yang, F. Meng, J. Zhang, M. O. Hasna and M. Di Renzo, "On the performance of RIS-assisted dual-hop UAV communication systems," *IEEE Trans. on Veh. Technol.*, vol. 69, no. 10, pp. 12 296–12 300, 2020.

[148] X. Mu, Y. Liu, L. Guo, J. Lin and H. V. Poor, "Intelligent reflecting surface enhanced multi-UAV NOMA networks," arXiv:2101.09145, 2021.

[149] X. Liu, Y. Liu and Y. Chen, "Machine learning empowered trajectory and passive beamforming design in UAV-RIS wireless networks," *IEEE J. on Sel. Areas Commun.*, 2020.

[150] Q. Liu, J. Wu, P. Xia, S. Zhao, W. Chen, Y. Yang and L. Hanzo, "Charging unplugged: Will distributed laser charging for mobile wireless power transfer work?" *IEEE Veh. Technol. Mag.*, vol. 11, no. 4, pp. 36–45, 2016.

[151] C. Pan et al., "Reconfigurable Intelligent Surfaces for 6G Systems: Principles, Applications, and Research Directions," *IEEE Commun. Mag.*, vol. 59, no. 6, pp. 14-20, June 2021.

[152] Y. Pan, K. Wang, C. Pan, H. Zhu and J. Wang, "Self-Sustainable Reconfigurable Intelligent Surface Aided Simultaneous Terahertz Information and Power Transfer (STIPT)," arXiv:2102.04053v1, 2021.

[153] Q. Wu and R. Zhang, "Weighted sum power maximization for intelligent reflecting surface aided SWIPT," *IEEE Wireless Commun. Lett.*, vol. 9, no. 5, pp. 586–590, 2019.

[154] Y. Tang, G. Ma, H. Xie, J. Xu and X. Han, "Joint transmit and reflective beamforming design for IRS-assisted multiuser miso swipt systems," in *IEEE Proc. of Int. Commun. Conf. (ICC)*, 2020, pp. 1–6.

[155] C. Pan, H. Ren, K. Wang, M. Elkashlan, A. Nallanathan, J. Wang and L. Hanzo, "Intelligent reflecting surface enhanced MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE J. on Sel. Areas Commun.*, vol. 38, no. 8, pp. 1719–1734, 2020.

[156] Q. Wu and R. Zhang, "Joint active and passive beamforming optimization for intelligent reflecting surface assisted SWIPT under QoS constraints," *IEEE J. on Sel. Areas Commun.*, vol. 38, no. 8, pp. 1735–1748, 2020.

[157] G. Zhou, C. Pan, H. Ren, K. Wang, M. Elkashlan and M. D. Renzo, "Stochastic Learning-Based Robust Beamforming Design for RIS-Aided Millimeter-Wave Systems in the Presence of Random Blockages," *IEEE Trans. on Veh. Technol.*, vol. 70, no. 1, pp. 1057-1061, Jan. 2021.

[158] Y. Yang, B. Zheng, S. Zhang and R. Zhang, "Intelligent reflecting surface meets OFDM: Protocol design and rate maximization," *IEEE Trans. on Commun.*, vol. 68, no. 7, pp. 4522–4535, 2020.

[159] N. S. Perovic, M. D. Renzo and M. F. Flanagan, "Channel capacity optimization using reconfigurable intelligent surfaces in indoor mmwave environments," *in Proc. IEEE ICC*, 2020, pp. 1–7.

[160] S. Mao et al., "Computation Rate Maximization for Intelligent Reflecting Surface Enhanced Wireless Powered Mobile Edge Computing Networks," *IEEE Trans. on Veh. Technol.*, vol. 70, no. 10, pp. 10820-10831, Oct. 2021.

[161] F. E. Bouanani, S. Muhaidat, P. C. Sofotasios, O. A. Dobre and O. S. Badarneh, "Performance analysis of intelligent reflecting surface aided wireless networks with wireless power transfer," *IEEE Commun. Lett.*, vol. 25, no. 3, pp. 793–797, Mar. 2021.

[162] Y. Liu, X. Mu, J. Xu, R. Schober, Y. Hao, H. V. Poor and L. Hanzo, "STAR: Simultaneous transmission and reflection for 360° coverage by intelligent surfaces," [Online]. Available: https://arxiv.org/abs/2103.09104.

[163] NTT DOCOMO, "DOCOMO conducts world's first successful trial of transparent dynamic metasurface," [Online]. Available: https://www.nttdocomo.co.jp/english/info/mediacenter/pr/2020/0117 00.html.

[164] Y. Liu, Z. Qin, M. Elkashlan, Y. Gao and L. Hanzo, "Enhancing the physical layer security of non-orthogonal multiple access in large-scale networks," *IEEE Trans. on Wireless Commun.*, vol. 16, no. 3, pp. 1656–1672, 2017.

[165] Y. Li, M. Jiang, Q. Zhang and J. Qin, "Joint beamforming design in multi-cluster MISO NOMA intelligent reflecting surface-aided downlink communication networks," arXiv:1909.06972, 2019.

[166] Y. Liu, X. Mu, X. Liu, M. D. Renzo, Z. Ding and R. Schober, "Reconfigurable Intelligent Surfaces (RIS) Aided Multi-user Systems: Interplay between NOMA and RIS," https://arxiv.org/abs/2011.13336, 2020.

[167] A. Makarf, K. M. Rabie, O. Kaiwartya, K. Adhikari, X. Li, M. Quiroz-Castellanos and R. Kharel, "Reconfigurable intelligent surfaces-enabled vehicular networks: A physical layer security perspective," arXiv:2004.11288, 2020.

[168] J. Wang, W. H. Zhang, X. Bao, T. Song and C. Pan, "Outage analysis for intelligent reflecting surface assisted vehicular communication networks," arXiv: 2005.00996, 2020.

[169] A. A. Hilo, M. Samir, M. Elhattab, C. Assi and S. Sharafeddine, "Reconfigurable Intelligent Surface Enabled Vehicular Communication: Joint User Scheduling and Passive Beamforming," https://arxiv.org/abs/2101.12247, 2021.

[170] S. Y. Park and D. In Kim, "Intelligent Reflecting Surface-aided Phase-Shift Backscatter Communication," *2020 14th Int. Conf. on Ubiquitous Inf. Manage. and Commun. (IMCOM)*, 2020, pp. 1-5.

[171] X. Jia and X. Zhou, "IRS-Assisted Ambient Backscatter Communications Utilizing Deep Reinforcement Learning," *IEEE Wireless Commun. Lett.*, 2021.

[172] H. Abumarshoud, L. Mohjazi, O. A. Dobre, M. Di Renzo, M. A. Imran and H. Haas, "LiFi through Reconfigurable Intelligent Surfaces: A New Frontier for 6G?," *IEEE Veh. Technol. Mag.*, vol. 17, no. 1, pp. 37-46, Mar. 2022.

[173] H. Abumarshoud, B. Selim, M. Tatipamula and H. Haas, "Intelligent Reflecting Surfaces for Enhanced NOMA based Visible Light Communications," arXiv:2111.04646, 2021.

[174] F. Hussain, S. A. Hassan, R. Hussain and E. Hossain, "Machine learning for resource management in cellular and IoT networks: Potentials, current solutions, and open challenges," *IEEE Commun. Surv. & Tut.*, vol. 22, no. 2, pp. 1251–1275, 2020.

[175] S. K. Das, M. Siddikur Rahman, L. Mohjazi, M. A. Imran and K. M. Rabie, "Reinforcement Learning-Based Resource Allocation for M2M Communications over Cellular Networks," *in Proc. IEEE WCNC*, 2022, pp. 1473-1478, Austin, TX, USA.

[176] A. Alwarafy, B. S. Ciftler, M. Abdallah and M. Hamdi, "DeepRAT: A DRL-based framework for multi-RAT assignment and power allocation in hetnets," *in Proc. IEEE ICC*, 2021, pp. 1–6.

[177] N. C. Luong, D. T. Hoang, S. Gong, D. Niyato, P. Wang, Y.-C. Liang and D. I. Kim, "Applications of deep reinforcement learning in communications and networking: A survey," *IEEE Commun. Surv. & Tut.*, 2019.

[178] Y. L. Lee and D. Qin, "A survey on applications of deep reinforcement learning in resource management for 5G heterogeneous networks," in *2019 IEEE Asia-Pacific Signal and Inf. Process. Assoc. Annu. Summit and Conf. (APSIPA ASC)*, 2019, pp. 1856–1862.

[179] M. Chen, U. Challita, W. Saad, C. Yin and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: A tutorial," *IEEE Commun. Surv. & Tut.*, vol. 21, no. 4, pp. 3039–3071, 2019.

[180] A. Zappone, M. Di Renzo and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, AI-based, or both?" *IEEE Trans. on Commun.*, vol. 67, no. 10, pp. 7331–7376, 2019.

[181] S. Yuan, Y. Zhang, W. Qie, T. Ma and S. Li, "Deep reinforcement learning for resource allocation with network slicing in cognitive radio network," *Comput. Sci. and Inf. Syst.*, vol. 18, no. 3, pp. 55– 55, 2020.

[182] Y. Zhang, X. Wang and Y. Xu, "Energy-efficient resource allocation in uplink noma systems with deep reinforcement learning," *in 2019 11th Int. Conf. on Wireless Commun. and Signal Process. (WCSP)*, 2019, pp. 1–6.

[183] C. He, Y. Hu, Y. Chen and B. Zeng, "Joint power allocation and channel assignment for NOMA with deep reinforcement learning," *IEEE J. on Sel. Areas in Commun.*, vol. 37, no. 10, pp. 2200–2210, 2019.

[184] Z. Jiang, C. Hao, Y. Huang, Q. Wu and F. Zhou, "Partially distributed channel and power management based on reinforcement learning," *J. of Commun. and Inf. Netw.*, vol. 5, no. 4, pp. 423–437, 2020.

[185] W. Saad, M. Bennis and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," *IEEE Netw.*, 2019.

[186] B. Das and S. Roy, "Load balancing techniques for wireless mesh networks: A survey," *in 2013 Int. Symp. on Comput. and Business Intell.*, 2013, pp. 247–253.

[187] L. Zhu, W. Shen, S. Pan, R. Li and Z. Li, "A dynamic load balancing method for spatial data network service," *in 2009 5th Int. Conf. on Wireless Commun., Netw. and Mobile Comput.*, 2009, pp. 1–3.

[188] H. Desai and R. Oza, "A study of dynamic load balancing in grid environment," *in 2016 Int. Conf. on Wireless Commun., Signal Process. and Netw. (WiSPNET)*, 2016, pp. 128–132.

[189] L. Ju, B. Geng, J. Horng et al., "Graphene plasmonics for tunable terahertz metamaterials", *Nature Nanotechol.*, vol. 6, no. 10, pp. 630-634, 2011.

[190] J. Feng, W. Zhang, Q. Pei, J. Wu and X. Lin, "Heterogeneous Computation and Resource Allocation for Wireless Powered Federated Edge Learning Systems", *IEEE Trans. on Commun.*, vol. 70, no. 5, pp. 3220-3233, May 2022.

[191] R. Karasik, O. Simeone, M. Di Renzo and S. Shamai Shitz, "Beyond max-SNR: Joint encoding for reconfigurable intelligent surfaces," *in 2020 IEEE Int. Symp. on Inf. Theory (ISIT)*, 2020, pp. 2965–2970.

[192] X. Mu, Y. Liu, L. Guo, J. Lin and N. Al-Dhahir, "Capacity and optimal resource allocation for IRS-assisted multi-user communication systems," *IEEE Trans. on Commun.*, 2021.

[193] S. Zhang and R. Zhang, "Intelligent reflecting surface aided multiple access: Capacity region and deployment strategy," *in 2020 IEEE 21st Int. Workshop on Signal Process. Adv. in Wireless Commun. (SPAWC)*, 2020, pp. 1–5.

[194] L. Li and A. J. Goldsmith, "Capacity and optimal resource allocation for fading broadcast channels .I. ergodic capacity," *IEEE Trans. on Inf. Theory*, vol. 47, no. 3, pp. 1083–1102, 2001.

[195] Y. Yang, S. Zhang and R. Zhang, "IRS-enhanced OFDMA: Joint resource allocation and passive beamforming optimization," *IEEE Wireless Commun. Lett.*, vol. 9, no. 6, pp. 760–764, 2020.

[196] J. Zuo, Y. Liu, Z. Qin and N. Al-Dhahir, "Resource allocation in intelligent reflecting surface assisted NOMA systems," *IEEE Trans. on Commun.*, vol. 68, no. 11, pp. 7170–7183, 2020.

[197] X. Li, J. Fang, F. Gao and H. Li, "Joint active and passive beamforming for intelligent reflecting surface-assisted massive MIMO systems," arXiv: 1912.00728, 2019.

[198] Z. Ding, X. Lei, G. K. Karagiannidis, R. Schober, J. Yuan and V. K. Bhargava, "A survey on non-orthogonal multiple access for 5G networks: Research challenges and future trends," *IEEE J. on Sel. Areas in Commun.*, vol. 35, no. 10, pp. 2181–2195, 2017.

[199] P. S. Bouzinis, P. D. Diamantoulakis and G. K. Karagiannidis, "Wireless federated learning (FL) for 6G Networks - Part II: The compute-thentransmit NOMA paradigm," *submitted to IEEE Commun. Lett.*, 2021.

[200] H. Xie, J. Xu and Y. F. Liu, "Max-min fairness in IRS-aided multi-cell MISO systems with joint transmit and reflective beamforming," *IEEE Trans. on Wireless Commun.*, vol. 20, no. 2, pp. 1379–1393, 2021.

[201] C.-X. Wang, M. Di Renzo, S. Stanczak, S. Wang and E. G. Larsson, "Artificial intelligence enabled wireless networking for 5G and beyond: Recent advances and future challenges," *IEEE Wireless Commun.*, vol. 27, no. 1, pp. 16–23, 2020.

[202] X. Wang, X. Wang and S. Mao, "Resloc: Deep residual sharing learning for indoor localization with CSI tensors," *in Proc. IEEE PIMRC 2017*, Montreal, Canada, Oct. 2017.

[203] N. D. Lane, S. Bhattacharya, A. Mathur, P. Georgiev, C. Forlivesi and F. Kawsar, "Squeezing deep learning into mobile and embedded devices," *IEEE Pervasive Comput.*, vol. 16, no. 3, pp. 82–88, July 2017.

[204] O. A. Wahab, A. Mourad, H. Otrok and T. Taleb, "Federated machine learning: Survey, multi-level classification, desirable criteria and future directions in communication and networking systems," *IEEE Commun. Surv. & Tut.*, pp. 1–1, 2021.

[205] N. H. Tran, W. Bao, A. Zomaya, M. N. Nguyen and C. S. Hong, "Federated learning over wireless networks: Optimization model design and analysis," *in Proc. IEEE INFOCOM*, 2019, pp. 1387–1395.

[206] S. Wang, T. Tuor, T. Salonidis, K. K. Leung, C. Makaya, T. He and K. Chan, "Adaptive federated learning in resource constrained edge computing systems," *IEEE J. on Sel. Areas in Commun.*, vol. 37, no. 6, pp. 1205–1221, 2019.

[207] X. Wang, C. Wang, X. Li, V. C. Leung and T. Taleb, "Federated Deep Reinforcement Learning for Internet of Things With Decentralized Cooperative Edge Caching," *IEEE Internet of Things J.*, vol. 7, no. 10, pp. 9441–9455, Oct. 2020.

[208] H. H. Zhuo, W. Feng, Q. Xu, Q. Yang and Y. Lin, "Federated reinforcement learning," arXiv preprint arXiv:1901.08277, 2019.

[209] C. Xie, S. Koyejo and I. Gupta, "Asynchronous federated optimization," arXiv preprint arXiv:1903.03934, 2019.

[210] S. Ali et. al., "6G white paper on machine learning in wireless communication networks," arXiv:2004.13875 [cs.IT], Apr. 2020.

[211] V. Savaux and Y. Louet, "LMMSE channel estimation in OFDM ¨ context: A review," *IET Signal Process.*, vol. 11, no. 2, pp. 123–134, Apr. 2017.

[212] Z. Gong, F. Jiang and C. Li, "Angle domain channel tracking with large antenna array for high mobility V2I millimeter wave communications,"

IEEE J. of Sel. Topics in Signal Process., vol. 13, no. 5, pp. 1077–1089, Aug. 2019.

[213] T. Li, M. R. A. Khandaker, F. Tariq, K. Wong and R. T. Khan, "Learning the wireless V2I channels using deep neural networks," *in IEEE 90th VTC-Fall*, Nov. 2019.

[214] R. Sattiraju, A. Weinand and H. D. Schotten, "Channel estimation in C-V2X using deep learning," arXiv:2003.02617, 2020.

[215] L. Oneto, S. Ridella and D. Anguita, "Quantum computing and supervised machine learning: Training, model selection, and error estimation," *Quantum Inspired Comput. Intell. Elsevier*, Chapter 2, 2017, pp. 33–83.

[216] W. Diffie and M. Hellman, "New directions in cryptography," *IEEE Trans. Inf. Theory*, vol. 22, no. 6, pp. 644–654, 1976.

[217] P. V. Trinh, A. T. Pham, A. Carrasco-Casado, and M. Toyoshima, "Quantum key distribution over FSO: Current development and future perspectives," *in Prog. in Electromagn. Res. Symp. (PIERS-Toyama)*, 2018, pp. 1672–1679..

[218] C. E. Shannon, "A mathematical theory of communication," *The Bell Syst. Tech. J.*, vol. 27, no. 3, pp. 379–423, 1948.

[219] P. Basu, J. Bao, M. Dean, and J. Hendler, "Preserving quality of information by using semantic relationships," *Pervasive Mob. Comput.*, vol. 11, pp. 188–202, Apr. 2014.

[220] N. Farsad, M. Rao, and A. Goldsmith, "Deep learning for joint source-channel coding of text," *in Proc. IEEE Int. Conf. Acoustics Speech Signal Process. (ICASSP)*, Calgary, AB, Canada, Apr. 2018, pp. 2326–2330.

[221] E. Bourtsoulatze, D. B. Kurka, and D. Gunduz, "Deep joint source-channel coding for wireless image transmission," *IEEE Trans. Cogn. Comm. Netw.*, vol. 5, no. 3, pp. 567–579, May 2019.

[222] H. Xie and Z. Qin, "A Lite Distributed Semantic Communication System for Internet of Things," *IEEE J. on Sel. Areas in Commun.*, vol. 39, no. 1, pp. 142-153, Jan. 2021.

[223] H. Xie, Z. Qin, G. Y. Li and B. -H. Juang, "Deep Learning Enabled Semantic Communication Systems," *IEEE Trans. on Signal Process.*, vol. 69, pp. 2663-2675, 2021.

[224] E. C. Strinati and S. Barbarossa, "6G networks: beyond Shannon towards semantic and goal-oriented communications," *Comput. Netw.,* vol. 190, 2021, 107930.