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SURVEY

Intelligent Massive MIMO Systems for Beyond 5G Networks: An Overview and Future Trends

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ABSTRACT Machine learning (ML) which is a subset of artificial intelligence is expected to unlock the potential of challenging large-scale problems in conventional massive multiple-input-multiple-output (CM-MIMO) systems. This introduces the concept of intelligent massive MIMO (I-mMIMO) systems. Due to the surge of application of different ML techniques in the enhancement of mMIMO systems for existing and emerging use cases beyond fifth-generation (B5G) networks, this article aims to provide an overview of the different aspects of the I-mMIMO systems. First, the characteristics and challenges of the CM-MIMO have been identified. Secondly, the most recent efforts aimed at applying ML to a different aspect of CM-MIMO systems are presented. Thirdly, the deployment of I-mMIMO and efforts towards standardization are discussed. Lastly, the future trends of I-mMIMO-enabled application systems are presented. The aim of this paper is to assist the readers to understand different ML approaches in CM-MIMO systems, explore some of the advantages and disadvantages, identify some of the open issues, and motivate the readers toward future trends.

INDEX TERMS 5G, 6G network, beyond 5G, artificial intelligence, deep learning, intelligent MIMO, machine learning, massive MIMO.

I. INTRODUCTION

In the fifth-generation (5G) network, massive multiple-input-multiple-output (mMIMO) was considered one of the key disruptive technologies. The intensive research effort over the past decade has made mMIMO a reality and has shown that it can meet the unprecedented high spectral and energy efficiency requirements compared to fourth-generation (4G) multi-user MIMO systems [1]. The concept of mMIMO is developed based on the deployment of very large numbers of antennas at the base station to serve simultaneously many terminals [2]. The research on mMIMO has spanned over a decade and it is still an active research area as more efforts are being made to meet the stringent requirements of beyond 5G (B5G) networks. The concepts of B5G networks are currently being discussed under different topics such as sixth-generation (6G), 2030 networks, and next-generation wireless networks. Some of the research articles have provided insights on what to expect from the B5G networks [3], [4], [5], [6], [7], [8], [9], [10], [11]. These include network capabilities for new market and industry verticals such as industry 4.0 autonomous applications, media and entertainment, healthcare systems, virtual reality, augmented reality, extended reality, and the education sector [6], [9]. Such new verticals will create massive-scale connectivity with disparate performance objectives such as ultra-high reliability,

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extremely high data rates, and ultra-low latency. While the conceptualization of the B5G and 6G are in progress, it is expected that artificial intelligence (AI) will play a vital role in the design and optimization of wireless communication systems, protocols, and operations. Tremendous success has been evidenced in the research and deployment of mMIMO. However, there are still issues that need to be addressed to transform mMIMO into a fully user-centric, scalable, flexible system to embrace emerging technologies in the B5G networks. The issues include computational complexity [12], scalability issues, resource allocation, and novel cellular use cases that are not feasible with mathematically or model-based approaches such as user positioning [13] and smart environments.

To address these issues, AI-driven mMIMO systems have attracted a great deal of research interest from both the industry and academia, paving the way for intelligent mMIMO (I-mMIMO) systems. The I-mMIMO integrates different AI techniques to address challenging and highly complex problems. AI techniques that involve the simulation of human intelligence by machines have been identified as a key enabling technique for I-mMIMO systems [14]. The branch of AI that has been largely exploited for wireless communication is machine learning (ML). The ML technique can be categorized into supervised, unsupervised, and reinforcement learning (RL). In particular, ML enables machines to learn from large amounts of data in order to perform certain tasks without explicitly programming it while deep learning (DL) is a technique for implementing ML by using multi-layer artificial neural networks (ANN). The use of ML is considered a valuable AI tool for assisting in intelligent, adaptive, and decision-making in communication technology. The ML is expected to unlock solutions to previously difficult and large-scale problems that are associated with mMIMO systems. However, an important factor to consider is the determination of the right use cases for ML in mMIMO communications. For the rest of this paper, we shall refer to the use of AI in mMIMO systems as the application of ML and its subset DL. Recent works have highlighted some key areas of the application of ML in mMIMO systems. This includes the physical layer (PHY) operations which are automatic modulation recognition, channel estimation (CE), signal detection, channel encoding and decoding, and beamforming [15], [16]. Other aspects include control of the PHY via configuration of multiple metasurfaces for redirection of the beam from the base station (BS) to hidden terminals, and lastly the management of mMIMO network for resource allocation [1], [17].

Some of the advantages of ML for mMIMO communication systems based on existing studies [16], [18], [19], [20], [21], [22] are summarized as follows:

1) The intrinsic ability of ML to learn, directly from the observed data, complex input-output relationships, and statistical structures facilitate dimensionality reduction thereby reducing computational time and complexity, and increase in spectral efficiency and energy efficiency in large-scale mMIMO systems.
2) Less complexity in dealing with non-linear characteristics that are often associated with the PHY layer due to hardware impairments from low-cost components or low-precision analog-to-digital converters (ADCs).
3) Overcome the limitations faced in the use of mathematical models and optimization problems in signal processing, especially in mathematically non-tractable problems.
4) Provide intelligence in network decision-making for user-centric services by taking into consideration both the signal processing and network environmental factors, such as channel dynamics, traffic patterns, quality of experience, and network composition.

In order to provide an overview of the application of ML in I-mMIMO systems, this article aims to address the following research questions (RQ) - RQ1: What are deployment methods for I-mMIMO systems? RQ2: What is the current research trend in the application of ML in I-mMIMO? RQ3: What are the challenges and open issues in the adoption of ML in I-mMIMO systems? RQ4: What are the future directions for ML in I-mMIMO systems?

A. RELATED WORKS AND MOTIVATION

Recent surveys in the literature have discussed the use of AI in communications systems [1], [14], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36]. In [1], Bjornson *et al.* highlighted five new research directions for mMIMO, among which one of them is the I-mMIMO systems. The authors illustrated how the use of ML can transform the conventional mMIMO system into an I-mMIMO system. In [14], the authors discussed the advantages that AI would provide for B5G communication networks. The need for ML in mMIMO and some examples of ML applications in mMIMO were discussed in the literature. A survey on the applications of deep reinforcement learning (DRL) in communications and networking was presented in [24]. Similarly, a survey on the application of DL in physical channel models with emphasis on automatic modulation recognition, channel decoding and detection was presented in [25]. In [22] Zappone *et al.*, provided a detailed discussion on the application of DL in wireless communication systems by establishing the link between ML and DL, and the application of DL models and mathematical models in wireless networks. A review of DL-based detectors for uplink communication in mMIMO systems was presented in [26] with a detailed discussion of various deep neural networks (DNN). While in [27] a tutorial on DRL as multi-agent learning in cooperative AI-enabled wireless networks was presented. Bhatia *et al.* [28] presented a short review of DL approaches for mMIMO systems. This includes DL for modulation recognition, beam selection, CE, and antenna selection (AS). A survey from Zhang and Zhu [29] identified six major areas for AI-enabled 6G networks. One of the areas includes advanced radio interfaces such as CE and detection, channel coding, modulation recognition, and end-to-end radio optimization. In [33], [35],

[36], and [34], the DL approach for PHY techniques such as the non-orthogonal multiple access (NOMA), mMIMO and millimeter wave (mmWave) communication were discussed. The advantages of the DL framework for the direction of arrivals (DoA) estimation and CE issues in mMIMO over other conventional schemes were presented. The authors in [35], [36], and [34] presented a survey on the applications of DL in the different layers of wireless networks, comprising PHY, medium access control, and network, while a tutorial on the ANN for wireless networks was presented in [34]. In summary, some of these works have discussed the general applications of AI and its subset in wireless communication technology [14], [22], [23], [27], [31], [33]. A few have highlighted the role of ML in mMIMO [1], [22], [26], [28], [33] with less review on the extensive existing work in the literature. To the best of our knowledge, no work has provided an overview of the plethora of work on the application of ML in mMIMO systems. To fill in this gap, a comprehensive survey of literature on the application of ML in I-mMIMO systems was carried out by conducting an advanced search to identify relevant literature using the Web of Science (WoS) database. The search focused on mapping the existing literature on the application of ML techniques in I-mMIMO systems. The summary of the related review papers is presented in Table 1. In this table, we analyze and compare the discussions from the related review and survey papers under the following criteria (C): C1-testbed and dataset, C2-Standardization, C3-channel estimation, C4-beamforming, precoding and decoding, C5-detection and modulation recognition, C6-power control, C7-resource allocation/handover mechanism, C8-low-bit ADC, C9-intelligent reflective surfaces, C10-user localization, and C11-mMIMO classification.

B. CONTRIBUTIONS

The contributions of this paper are outlined as follows:

- We discuss the CM-MIMO under two categories cellular-based mMIMO (C-mMIMO) and cell-free based mMIMO (CF-mMIMO). The challenges and limitations of the C-mMIMO are identified and discussed in detail.
- We discuss the fundamental details of the deployment of I-mMIMO systems and efforts toward standardization.
- We provide an overview of research areas related to I-mMIMO systems and open research issues.
- We outline future trends and identify research directions for achieving I-mMIMO systems for B5G networks.

C. ORGANIZATION

The remainder of this paper is structured as follows. In Section II, the different mMIMO approaches are presented under two forms: C-mMIMO and CF-mMIMO systems. The challenges of the CM-MIMO are presented in Section III while the overview of ML in mMIMO is discussed in Section IV. In Section V, the deployment strategies for the I-mMIMO systems are presented and Section VI provides a review of the applications of ML in various aspects of the I-mMIMO systems. The open issues are identified in Section VII and future directions are discussed in Section VIII. Finally, Section IX concludes the paper.

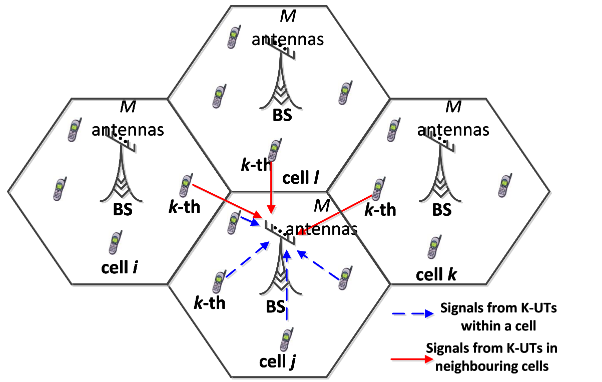

FIGURE 1. Illustration of co-located mMIMO system [2].

II. MASSIVE MIMO APPROACH

The mMIMO is one of the key enabling technologies for 5G and B5G networks, where large arrays of antennas are deployed at the BS for spatial multiplexing and high beamforming gain. The advantages of such technology are high spectral and energy efficiency. We discuss the conventional mMIMO under two categories: C-mMIMO and CF-mMIMO. The uplink and downlink transmission for the two types of mMIMO systems are presented in this section.

A. CELLULAR-BASED MASSIVE MIMO SYSTEM

The C-mMIMO are discussed under two types: the co-located mMIMO systems and the distributed antenna system (DAS) mMIMO systems.

1) CO-LOCATED mMIMO

In the co-located mMIMO system, the BS is equipped with a large number of antennas that collectively serves a number of user terminals (UTs) using the same time-frequency resource. The number of BS antenna M is greater than the number of UTs K in the service area. This facilitates the benefit of averaging out small-scale fading, reduced transmit power, and increased degree of freedom. The co-located mMIMO exploits the phenomenon known as channel hardening[1] which results in favorable channel propagation between BS and UTs [38]. The illustration of the co-located mMIMO systems is shown in Fig. 1.

Two types of transmission modes have been largely explored in the mMIMO systems: TDD and frequency division duplex (FDD). In the TDD transmission mode, channel reciprocity is assumed between the BS and the UT, where the BSs obtain the downlink channel directly from the uplink channel pilots transmitted by the UTs in the same frequency. The overhead scales with the number of users and it introduces constraint of coherence time. In the FDD, different

[1] Channel hardening is an effect where the channel variation decreases and becomes much more deterministic [37].

TABLE 1. Summary of related review papers on ML in mMIMO systems.

Ref	Year	Focus of ML	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Bjï¿œrnson *et al.* [1]	2019	mMIMO antenna arrays	×	×	✓	✓	×	×	×	✓	✓	✓	×
Wang *et al.* [14]	2020	Wireless networks B5G	×	×	✓	×	×	×	×	×	×	×	×
Jiang *et al.* [23]	2016	Next generation wireless networks	×	×	✓	×	×	×	×	×	×	×	×
Luong *et al.* [24]	2019	Communications and networking	×	×	✓	×	✓	✓	✓	×	×	✓	×
Wang *et al.* [25]	2017	Physical layer	×	×	✓	✓	✓	×	×	×	×	×	×
Zappone *et al.* [22]	2019	Wireless networks	×	×	✓	✓	✓	✓	✓	×	×	✓	×
Albreem *et al.* [26]	2021	mMIMO uplink detector	×	×	✓	×	✓	×	×	×	×	×	×
Feriani and Hossain [27]	2021	Wireless networks	×	×	×	✓	×	×	×	×	✓	×	×
Bhatia *et al.* [28]	2020	mMIMO systems	×	×	✓	✓	✓	×	✓	×	×	✓	×
Zhang and Zhu [29]	2020	6G networks	×	×	✓	✓	✓	×	✓	×	×	×	×
Chataut and Akl [30]	2020	mMIMO systems for B5G	×	×	✓	✓	✓	×	✓	×	×	×	×
Arjoune and Faruque [31]	2020	5G wireless systems	×	×	✓	✓	✓	×	✓	×	×	×	×
Huang *et al.* [33]	2019	Physical layer 5G wireless networks	×	×	✓	✓	✓	×	×	×	×	×	×
Pham *et al.* [32]	2021	Intelligent radio signal processing	×	✓	✓	✓	✓	×	×	×	×	×	×
This paper	2022	Intelligent mMIMO systems	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

C1-testbed and dataset, C2-Standardization, C3-channel estimation, C4-beamforming, precoding and decoding, C5-detection and modulation recognition, C6-power control, C7-resource allocation/handover mechanism, C8-low-bit ADC, C9-intelligent reflective surfaces, C10-user localization and C11-mMIMO classification.

frequency bands are used for uplink and downlink. In the downlink, the BS transmits the pilots to the UTs. Then, the UTs estimate the channel using these pilots and feedback their CE to the BS. In the uplink, the reverse is performed. This introduces some overheads that scale with the number of BS antennas and the constraint of limited bandwidth. The system model of the co-located uplink mMIMO system is expressed as [38]:

$$\boldsymbol{y}_j = \sum_{l=1}^{L}\sum_{k=1}^{K_l} \boldsymbol{h}_{lk}^{j} s_{lk} + \boldsymbol{n}_j \tag{1}$$

where $\boldsymbol{y}_j \in \mathbb{C}^{M_j}$ is the received signal at BS j and $\boldsymbol{n}_j \sim \mathcal{CN}(\mathbf{0}_{M_j}, \sigma_{UL}^2 \boldsymbol{I}_{M_j})$ is an independent additive receiver noise with zero mean and variance σ_{UL}^2, $s_{lk} \in \mathbb{C}$ is the uplink signal sent by the UT k in cell l with transmit power $p_{lk} = \mathbb{E}\{|s_{lk}|^2\}$ and $\boldsymbol{h}_{lk}^{j}$ is the channel vector between BS j and UT k in cell l. A receive combining vector $\boldsymbol{v}_{jk} \in \mathbb{C}^{M_j}$ is used at the BS j to separate the desired signal received from kth UT from interfering signals and expressed as:

$$\boldsymbol{v}_{jk}^{\mathrm{H}}\boldsymbol{y}_j = \underbrace{\boldsymbol{v}_{jk}^{\mathrm{H}}\boldsymbol{h}_{jk}^{j} s_{jk}}_{\text{Desired signal}} + \underbrace{\sum_{\substack{i=1\\ i\neq k}}^{K_j} \boldsymbol{v}_{jk}^{\mathrm{H}}\boldsymbol{h}_{ji}^{j} s_{ji}}_{\text{Intra-cell interference}} + \underbrace{\sum_{\substack{l=1\\ l\neq j}}^{L}\sum_{i=1}^{K_l} \boldsymbol{v}_{jk}^{\mathrm{H}}\boldsymbol{h}_{li}^{j} s_{li}}_{\text{Inter-cell interference}} + \underbrace{\boldsymbol{v}_{jk}^{\mathrm{H}}\boldsymbol{n}_j}_{\text{Noise}}. \tag{2}$$

The received signal $y_{jk} \in \mathbb{C}$ from the downlink transmission from the BS in cell j to the UT k is expressed as [38]:

$$y_{jk} = \sum_{l=1}^{L} (\boldsymbol{h}_{jk}^{l})^{H} \boldsymbol{X}_l + n_{jk} \tag{3}$$

where $n_{jk} \sim \mathcal{CN}(0, \sigma_{DL}^2)$ is independent additive receiver noise with σ_{DL}^2 and $\boldsymbol{X}_l = \sum_{i=l}^{K_l} \boldsymbol{w}_{li}\varsigma_{li}$ is the downlink signal transmitted by the BS in cell l. The received signal y_{jk} can be further expressed as:

$$\begin{aligned} y_{jk} &= \sum_{l=1}^{L}\sum_{i=1}^{K_l} \left(\boldsymbol{h}_{jk}^{l}\right)^{\mathrm{H}} \boldsymbol{w}_{li}\varsigma_{li} + n_{jk} \\ &= \underbrace{\left(\boldsymbol{h}_{jk}^{j}\right)^{\mathrm{H}} \boldsymbol{w}_{jk}\varsigma_{jk}}_{\text{Desired signal}} + \underbrace{\sum_{\substack{i=1\\ i\neq k}}^{K_j} \left(\boldsymbol{h}_{jk}^{j}\right)^{\mathrm{H}} \boldsymbol{w}_{ji}\varsigma_{ji}}_{\text{Intra-cell interference}} \\ &\quad + \underbrace{\sum_{\substack{l=1\\ l\neq j}}^{L}\sum_{i=1}^{K_l} \left(\boldsymbol{h}_{jk}^{l}\right)^{\mathrm{H}} \boldsymbol{w}_{li}\varsigma_{li}}_{\text{Inter-cell interference}} + \underbrace{n_{jk}}_{\text{Noise}}. \end{aligned} \tag{4}$$

where $\boldsymbol{w}_{li} \in \mathbb{C}^{M_l}$ is the transmit precoding vector and $\varsigma_{jk} \sim \mathcal{CN}(0, p_{lk})$ is the signal sent from the BS j to the UT k.

2) DAS mMIMO

The DAS mMIMO is another approach to achieving the gains of mMIMO. In DAS mMIMO system, remote antenna

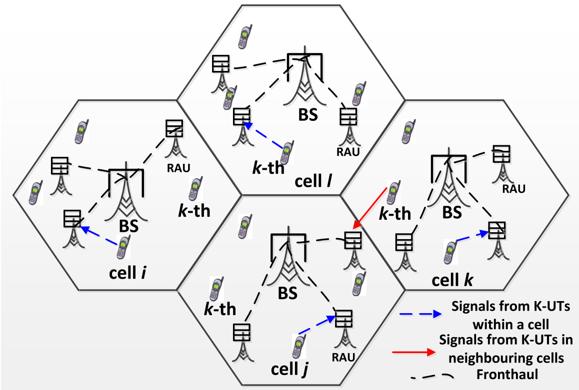

FIGURE 2. Illustration of DAS mMIMO systems.

units (RAUs) are distributed in a cell and connected to the BS via backhaul links [39], [40], [41] as shown in Fig. 2. The DAS mMIMO offers several advantages such as improved systems coverage, energy efficiency, and battery life of UTs due to the reduced access distance of the UTs and micro diversity [39], [40], [42], [43]. It can overcome large-scale fading (path loss) by reducing the physical transmission distance between the transmitter and the receiver. In addition, it helps to overcome the constraints in the form factor for a large number of antennas operating in sub-6 GHz [44]. A multi-cell system with L number of cells where each cell consists of M RAUs that are equipped with N antennas and K UTs. The system configuration for the DAS mMIMO is (M, N, K) while the system configuration for the co-located mMIMO is $(1, N, K)$.

Despite its several benefits, there are several challenges associated with the DAS mMIMO system. These include high demand for backhaul capacity (e.g., high capacity and low latency), higher complexity, increased synchronization requirements, more CE effort, and increased overhead [45], [46]. The concept of DAS mMIMO has been explored in the literature under different schemes such as distributed mMIMO [47], coordinated multipoint with joint transmission MIMO (CoMP-JT) [45], [48], network MIMO [49], [50], cooperative networks [51], and virtual network [52].

B. CELL-FREE MASSIVE MIMO

The idea of network MIMO has recently been reintroduced and extended to mMIMO as cell-free massive MIMO (CF-mMIMO) [53]. The CF-mMIMO is a form of network MIMO that employs a large number of distributed antennas, known as access points (AP), spread across a large coverage area [54]. By removing cell boundaries in conventional cellular networks, the APs are connected to central processing units (CPU) via fronthaul. The fronthaul carries quantized signals from the APs to the CPU. The concept eliminates the need for cellular connectivity so that all UTs can be supported by all APs over the same resources using network MIMO techniques to avoid mutual inter-cell interference [55]. Fig. 3 illustrates the concept of the CF-mMIMO.

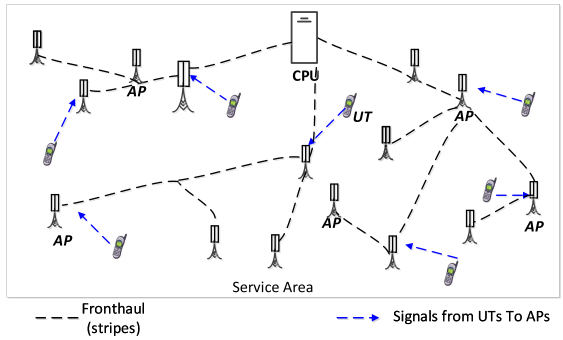

FIGURE 3. Illustration of cell-free mMIMO.

In the CF-mMIMO, it is assumed that the geographical area is not partitioned into cells but a random number of APs M are distributed in the coverage area which covers K UTs with single antenna where $M \gg K$.

The channel coefficient $\boldsymbol{g}_{mk}$ from the UT k to the AP m is expressed as [56]:

$$\boldsymbol{g}_{mk} = \sqrt{\beta_{mk}}\boldsymbol{h}_{mk}, \tag{5}$$

where β_{mk} is the large-scale fading factor which accounts for path loss and shadowing effects and $\boldsymbol{h}_{mk}$ is the small-scale fading coefficient and is expressed as $\boldsymbol{h}_{mk} \sim \mathcal{CN}(0, \boldsymbol{I}_N)$ [53]. The channel matrix between the APs and UTs is expressed as $G \in \mathbb{C}^{M \times K}$.

1) UPLINK TRANSMISSION

The uplink transmission from the UTs to the APs is classified into two types: uplink training and uplink payload data transmission. The uplink training is described as follows. All UTs transmit plot sequence $\mathbf{s_1}, \cdots, \boldsymbol{s}_K \in \mathbb{C}^{\tau}$ simultaneously and synchronously to all M APs within the service area. The pilot sequence transmitted assigned to all the UTs $\tau \times K$ are assumed to be orthogonal satisfying $\mathbf{s}_i^H \mathbf{s}_j = \delta_{ij}$ and the transmitted signal from the kth user to the AP is represented as $x_k = \sqrt{q_k} s_k$, where $\mathbb{E}\{|s_k|^2\} = 1$. The received signal sequence at the mth AP is expressed as:

$$\boldsymbol{y}_m = \sqrt{\rho_r \tau} \sum_{k=1}^{K} \boldsymbol{g}_{mk} \sqrt{q_k} \boldsymbol{s}_k + \boldsymbol{n}_m, \tag{6}$$

where ρ_r represents the normalized signal-to-noise ratio (SNR) of each pilot sequence and $\boldsymbol{n}_m \sim \mathcal{CN}(0, I_\tau)$ is additive noise and τ is the length of pilot sequences.

Each AP m obtains an estimate of the channel $\hat{g}_{mk}$ from all the UTs by computing the minimum mean square error (MMSE) estimate of g_{mk}. The $\hat{g}_{mk}$ is expressed as [56]:

$$\hat{g}_{mk} = c_{mk} \left(\sqrt{\rho_r \tau} \boldsymbol{g}_{mk} + \sqrt{\rho_r \tau} \sum_{k' \neq k}^{K} \boldsymbol{g}_{mk'} \boldsymbol{s}_k^H \boldsymbol{s}_{k'} + \boldsymbol{n}_{mk} \right), \tag{7}$$

where $\boldsymbol{n}_{mk}$ is the noise sequence at the mth antenna and c_{mk} is expressed as:

$$c_{mk} = \frac{\sqrt{\rho_r \tau} \beta_{mk}}{\tau \rho_r \sum_{k'=1}^{K} \beta_{mk'} \left| \boldsymbol{s}_k^H \boldsymbol{s}_{k'} \right|^2 + 1}. \tag{8}$$

The $\hat{g}_{mk}$ in (1) is obtained at the APs to determine the receiver coefficients and power allocation which are sent to the CPU.

The uplink payload data is described as follows. In the uplink, the K UTs transmit data simultaneously to the APs where the received signal at the mth AP is expressed as:

$$\boldsymbol{y}_m^u = \sqrt{\rho_u} \sum_{k=1}^{K} \boldsymbol{g}_{mk} \sqrt{\varsigma_k} \boldsymbol{q}_k + \boldsymbol{n}_{u,k} \tag{9}$$

where ρ_u is the normalized uplink SNR and $\boldsymbol{n}_{u,k} \sim \mathcal{CN}(0, 1)$ is additive noise at the mth AP, and q_k is the symbol transmitted by the kth UT. The AP detects the q_k using the conjugate of its (locally obtained) channel estimate $\hat{g}_{mk}$ from (7). The received signal at the CPU is expressed as:

$$R_u = \sum_{m=1}^{M} \hat{g}_{mk}^* y_m^u \tag{10}$$

2) DOWNLINK TRANSMISSION

During the downlink transmission, the payload data from the APs are sent to the K UTs by using the conjugate beamforming of the channel estimates obtained in the uplink training. The mth AP transmits signals x_m to the UTs, where x_m is expressed as:

$$x_m = \sqrt{\rho_d} \sum_{k=1}^{K} \sqrt{\varsigma_{mk}} \hat{g}_{mk}^* q_k,$$

where q_k is the information intended for UT k which satisfies $\mathbb{E}\{|q_k|^2\} = 1$, ρ_d is the transmit power limit of each AP and $\hat{g}_{mk}^*$ represents the precoding factor, namely the conjugate of the channel estimate between AP m and UT k. The ς_{mk}, $m = 1, \ldots, M$, $k = 1, \ldots K$ is the power control coefficient chosen to satisfy the following power constraints at each AP $\mathbb{E}\{|x_m|^2\} \leq \rho_d$. The received signal obtained at the kth UT is expressed as:

$$y_k^d = \sum_{m=1}^{M} g_{mk} x_m + n_{d,k}, \tag{11}$$

where $n_{d,k} \sim \mathcal{CN}(0, 1)$ is the additive noise.

The comparison between the different types of mMIMO systems is shown in Table 2.

III. CHALLENGES AND LIMITATIONS OF THE CM-MIMO SYSTEMS

Some of the challenges related to C-mMIMO have been discussed in [30] and [1]. We elaborate on some of the issues and discuss further issues relating to both C-mMIMO and CF-mMIMO. We cover CE, pilot contamination, hardware impairments, scalability, UT scheduling, and novel use cases for B5G wireless networks.

A. COMPUTATIONAL COMPLEXITY

Accurate and timely CE plays an important role in the performance of mMIMO systems. There are several factors that need to be considered while carrying out CE. These include 1) the type of transmission mode used either TDD or FDD, 2) the CE method adopted either training sequence (also known as pilot signal), blind (data aided) and semi-blind based techniques [2], 3) channel estimators, and 4) channel models. In CM-MIMO systems, the estimated channels are used for link scheduling by employing a model-based approach. The model-based approach is known to be computationally complex and finding the optimal scheduling solution is computationally complex for real-time implementation [57]. This introduces the constraints of channel state information (CSI) overhead and limited feedback bandwidth which reduces spectral efficiency. Furthermore, the accuracy of the CSI is affected by different factors such as channel aging caused by the random variation of the propagation channel. This makes the CSI different from when the channel is estimated and when it is used for precoding or detection. In addition, due to the large numbers of antennas and RF chains, coupled with fast time-varying and non-stationary characteristics of the channel, CE in high mobility environment is a great challenge. To date, the high signal acquisition costs and increased CSI estimation accuracy in mMIMO systems can be addressed by exploiting the spatial, temporal, and bi-directional channel correlations [58], [59], [60]. Several precoding and detection algorithms both linear and non-linear have been investigated for the mMIMO scheme such as the maximum ratio combining (MRC), zero- forcing (ZF), and minimum mean square error (MMSE). Optimal detection algorithms such as ML, ZF, and MMSE, as mentioned in [61], give excellent throughput performance under ideal assumptions, but they impose significant computational complexity due to the need for costly matrix inversion of a large dimension.

B. PILOT CONTAMINATION

In C-mMIMO or CF-mMIMO systems, channel estimates at the BS are obtained using pilot signals. Due to the limited pilot resources and coherence time, the pilot signals are reused in the TDD mMIMO systems which introduce the phenomenon known as pilot contamination [62]. Although [63] has shown that pilot contamination does not limit the mMIMO systems, methods to mitigate the effect of pilot contamination are still required to improve the network performance of mMIMO systems [64], [65]. For instance, the use of DL-aided channel estimation was proposed in [65] to reduce the influence of pilot contamination. Furthermore, pilot contamination attack is considered another issue and has been investigated in [66] and [67]. Hence, the use of ML techniques has been considered a useful method in the detection of spoofing and eavesdropper attacks in mMIMO systems.

TABLE 2. Comparison of CM-MIMO.

	Cellular mMIMO	Cell-free mMIMO	Intelligent mMIMO
Features	1. Employs large scale co-located or distributed antennas. BS are located in cells but no cooperation among the BS.	1. Employs networked APs which are connected to the CPU via fronthaul links. There are no cells but service area.	Employs AI-based and model based techniques in CM-MIMO.
Advantages	1. Reduced overhead for data sharing and limited fronthaul requirements in co-located antennas. 2. In distributed antenna systems, high diversity gain. 3. Benefits from channel hardening.	1. Eliminates multi-user interference. 2. Offers high energy efficiency compared to cellular mMIMO. 3. Better quality of service and uniform SE coverage, improved edge data rate.	1. Reduction in the computational complexity in cellular and CF-mMIMO. 2. Takes into account environmental parameters as well as signal processing for prediction of blockage and proactive handover.
Disadvantages	1. Co-located antenna systems suffer from intercell interference. 2. Does not provide uniform SE and coverage (co-located antenna systems).	1. Practical constraints of network synchronization and the requirements of a low-latency, fronthaul signaling for CSI and data sharing. 2. High computational complexity at the CPU.	1. Requires large data set for training 2. There might be a need for further training when the scenario changes.

C. SCALABILITY ISSUES

One of the design considerations in the implementation CF-mMIMO is the sharing of CSI and data of UTs between cooperating APs and the CPUs. This creates a scalability issue in the implementation of CF-mMIMO for large networks with many UTs. The three scalability issues identified in [68] are: 1) data processing needed at the APs for every data sent from the CPU via the APs to the UTs resulting in unsustainable computational complexity at the APs, 2) limitation of the CPU to scale as more APs are connected to the CPU, and 3) the issue of computation of the power control coefficient associated with some UT and some APs which depends on the channel statistics of UT-AP pairs [69]. In addition, the CF-mMIMO is faced with the challenge of the limited capacity of the fronthaul links needed for sending baseband samples, and control signaling connecting the APs to the CPU [70].

D. HARDWARE IMPAIRMENT

In mMIMO systems, due to the large antenna arrays, the use of inexpensive transceiver components is advocated. There are known hardware impairments faced in mMIMO systems from the use of inexpensive transceiver components which are non-linearity in low-noise amplifiers, phase-noise I/Q imbalance, and ADC quantization noise [71], [72]. For instance, low-resolution ADCs cause significant distortions in the received signals in the mMIMO systems [73], [74]. These impairments introduce non-linear distortion which can be estimated using appropriate functions with a parameterized model where the parameters are estimated via measurements. The limitation of such an approach of using explicit modeling or parameter estimation is that it is prone to propagation errors [16].

E. RESOURCE ALLOCATION

Most of the studies on mMIMO have considered the simultaneous transmission of UTs to the AP or BS. However, in practice, some UTs perform uplink transmission while other UTs receive downlink transmission from the BS or AP [75]. Due to the limited resources, only a subset of the UTs are selected from the total number of UTs and served simultaneously at any given time. In addition, the large arrays of antennas at the BS or AP requires splitting in order for some antennas to work in uplink mode while others work in downlink mode. This introduces the problem of optimal scheduling of UTs and suitable antenna splitting for optimal spectral efficiency to be achieved in the service area [75]. The model-based approach used in the CM-MIMO is considered to be resource-intensive and computationally hard, especially for dense networks where interfering signals need to be estimated first before optimal scheduling is carried out for the UTs [57]. Furthermore, the need to meet the requirement of UTs with different quality of service (QoS), traffic characteristics and dynamic channel states require smart allocation of resources in order to maximize system throughput [76]. This makes scheduling not only just computationally complex but also makes the practical implementation complex [77].

F. NOVEL CELLULAR USE CASES

The application of mMIMO in some novel use cases in B5G communication systems is discussed in this section. The challenges of CM-MIMO are also highlighted.

1) SMART ENVIRONMENT

There is now a paradigm shift from the traditional approach that focuses only on programming just the transmitter and receiver platforms to the programming of the radio propagation environment. This involves the use of ML for optimizing array aperture by providing high spatial beam resolution to locations with high UT density and lower resolutions to lower UT density. In addition, smartly control metasurfaces based on array position and geometry to overcome the challenges of blockage in order to achieve an ultra-reliable network. This has opened up research into intelligent radio environments (IRE) where AI is used for the control, programming, and optimization of wireless networks. In addition, the ability to apply ML in CSI combined with other information such as UT locations, and UT ID can be used to predict downlink

CSI from uplink CSI, predict RF resources needed based on UT behaviors, and positioning of UTs is seen to enhance the performance of the mMIMO systems. An example is the use of ML to enhance the feedback codebook aided by environmental knowledge for mMIMO systems [78].

2) LOCATION-AWARE AND CONTEXTUAL SERVICES

There are several location-based services with standard requirements for accuracy, latency, and energy consumption that depends on the transmitting energy, signal bandwidth, network geometry, and channel conditions. The standard requirement for different 5G location and positioning services is specified in the 3rd generation partnership project (3GPP) release 16 [79]. The use of C-mMIMO has been explored for user positioning and location by making use of channel measurement parameters such as angle-of-arrival (AoA), time-of-arrival (ToA), and/or received signal strength (RSS), angle-of-departure (AoD) [80], [81], [82]. In the C-mMIMO a number of BS are used as reference wireless nodes known as multi-anchor nodes [83] to infer the position of the UTs. A two-step approach is used to determine the location of the UTs. First, measurement of the channels between the anchor nodes and the mobile UTs is carried out and the measurement parameters AoA, AoD, and ToA are obtained. Then localization and mapping algorithms are used to determine the location of the mobile UTs. The algorithms for determining the positioning and mapping are computationally challenging due to non-linear problems in mMIMO systems [1], [84]. In addition, the process of estimating the position of UT from intermediate parameters AoA, ToA, and AoD is described in [85] as sub-optimum based on the theory of information processing inequality. The use of multi-anchor nodes introduces the challenge of clock synchronization between the BSs and the UTs. Hence, the use of a single-anchor for localization and synchronization has been proposed and investigated in [86] and [85]. For instance in the CF-mMIMO, where the CPU acts as a single anchor node for the entire service area, the CPU doubles as both a communication and localization processing unit [85]. This introduces the challenge of a trade-off between estimation accuracy and computational complexity.

IV. OVERVIEW OF ML IN mMIMO

In this section, we discuss the fundamentals of ML and some of the aspects of ML techniques that are exploited in the mMIMO systems to address different challenges. The ML techniques can be categorized into supervised learning, unsupervised learning, and reinforcement learning. Fig. 4 shows the classification and examples of some of the ML techniques.

A. SUPERVISED LEARNING

Supervised learning is highly attractive for channel estimation, beam tracking, user localization, and other applications in mMIMO systems. In supervised learning, each training sample has an input and a corresponding desired output where the latter is referred to as a label. Using the labeled training set, the supervised learning algorithm aims to provide the desired result. Supervised learning problems can be generally classified into two classes: regression problems and classification problems. In the former, the algorithm aims to provide a continuous valued output whereas in the latter the algorithm aims to provide a label or discrete-valued output.

A supervised learning framework can be mathematically described as follows:

$$h : \tilde{\boldsymbol{x}} \rightarrow \tilde{\boldsymbol{y}}, \tag{12}$$

where $h : \mathbb{R}^n \times \mathbb{R}^k$ is a mapping function, $\tilde{\boldsymbol{x}}$ is an input vector with n dimension (which is also known as features), and $\tilde{\boldsymbol{y}}$ is an output vector in k dimension. Some examples of the input vector in mMIMO systems are the real and imaginary parts of the channel coefficients, index of the beam over a period of time, and antenna selection vector, while some examples of the output vector are the predicted channel coefficients, blockage probability, and optimal antenna selection vector [87], [88], [89].

By using training set $\mathcal{M}$, a well-designed h that best maps an input $\tilde{\boldsymbol{x}}$ to an output $\tilde{\boldsymbol{y}}$ can be established. In the training set $\mathcal{M}$, the ith training sample can be denoted as $\boldsymbol{x}^{(i)} = \left[x_1^{(i)}, \ldots, x_n^{(i)}\right]^T$, the jth feature of the ith training sample is denoted as $x_j^{(i)}$, and $\boldsymbol{y}^{(i)}$ is the corresponding labels of $\boldsymbol{x}^{(i)}$. The training samples in mMIMO studies can be obtained by using the model-driven approach, ray tracing, or dataset generated from DL frameworks [90].

In general, there are many ways to model h but the best model depends on the problem, training set, and design concerns. For example, h can be defined by using the following iterative functions:

$$\boldsymbol{a}^{[l]} = g_l\left(\boldsymbol{W}^{[l]}\boldsymbol{a}^{[l-1]} + \boldsymbol{b}^{[l]}\right), \quad l = 1, \ldots, L \tag{13}$$

where $g_l(\cdot)$ is an element-wise non-linear activation function, $\boldsymbol{W}^{[l]}$ is a weight matrix and $\boldsymbol{b}^{[l]}$ is a bias vector. In (13), $\boldsymbol{a}^{[0]} = \tilde{\boldsymbol{x}}$ is the input vector and $\boldsymbol{a}^{[L]} = \tilde{\boldsymbol{y}}$ is the output vector. The above iterative functions are referred to as the fully-connected deep neural networks (DNN). Nevertheless, researchers are exploring different types of neural networks such as recurrent neural networks (RNN), convolution neural network (CNN), and graph neural network (GNN) as well as their combinations.

In addition, the weight matrix and biased vector, which are referred to as the parameters, determine the mapping function and the supervised learning's efficiency. To obtain the best parameters, cost function J and loss function $\mathcal{L}$ are employed. The cost function J indicates the overall performance of the mapping function based on the given training set $\mathcal{M}$ while the loss function $\mathcal{L}$ measures the error of a single training sample. For instance, the cost function is modeled as follows:

$$J_{\mathcal{M}}(\tilde{\boldsymbol{w}}) = \frac{1}{M}\sum_{i=1}^{M} \mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right), \tag{14}$$

where $M = \mathrm{card}(\mathcal{M})$ is the total training samples. For example, in a regression problem, the loss function can be modeled

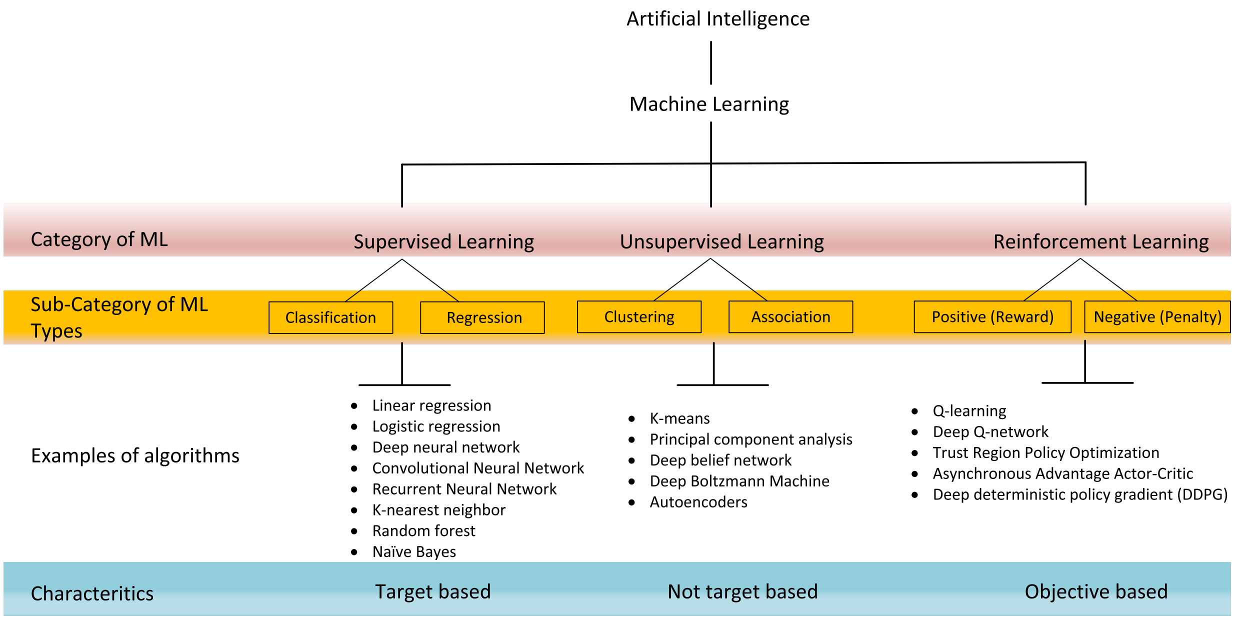

FIGURE 4. Summary of various ML techniques.

using the square error as follows:

$$\mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right) = \left(h_{w}\left(\boldsymbol{x}^{(i)}\right) - y^{(i)}\right)^2 \tag{15}$$

while the loss function in the classification problem can be modeled using a binary cross entropy as follows:

$$\mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right) = y^{(i)} \log\left(h_{w}\left(\boldsymbol{x}^{(i)}\right)\right) + \left(1-y^{(i)}\right) \log\left(1-h_{w}\left(\boldsymbol{x}^{(i)}\right)\right). \tag{16}$$

Other loss functions can also be adopted. Using the cost function J and training set $\mathcal{M}$, the optimal parameters can then be obtained via optimization algorithms such as stochastic gradient descent.

Fig. 5 shows a general supervised learning framework. As seen in Fig. 5, the fundamental principle of supervised learning is to leverage the training set and obtain the best parameters which minimize the cost function so that the parameters produce the best possible mapping function. Given an arbitrary $\tilde{\boldsymbol{x}}$, the supervised learning algorithm may use h to successfully provide the desired output $\tilde{\boldsymbol{y}}$.

B. UNSUPERVISED LEARNING

In unsupervised learning, each training sample only has an input and thus the data is referred to as unlabeled data. Using the unlabeled training set, an unsupervised learning algorithm aims to autonomously discover the structures and properties of the input data set. Thus, unsupervised learning can be used for dimension reduction, pattern search and clustering, which are suitable for user grouping [91], channel feedback [92], and other similar applications.

In this paper, we discuss two popular algorithms namely the K-means algorithm and principal component

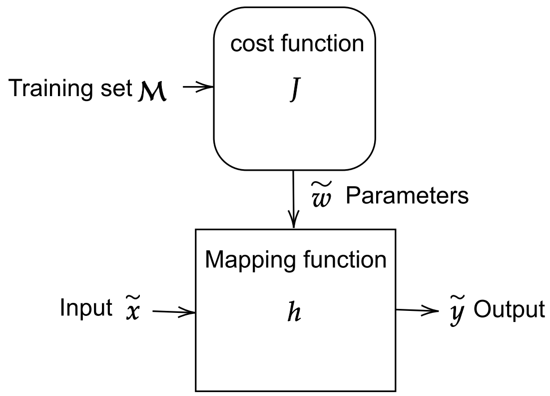

FIGURE 5. Supervised learning framework.

analysis (PCA). The K-means algorithm is a centroid-based model which is useful to autonomously categorize the input vector into K number of clusters. To cluster the input efficiently, the cost function can be formulated as follows:

$$J\left(\boldsymbol{c}, \boldsymbol{N}\right) = \frac{1}{M}\sum_{i=1}^{M}\left\|\boldsymbol{x}^{(i)} - \boldsymbol{\nu}^{c^{(i)}}\right\|^2, \tag{17}$$

where $\boldsymbol{c} = \left[c^{(1)}, \ldots, c^{(M)}\right]^T$ and $\boldsymbol{N} = \left[\boldsymbol{\nu}^{(1)}, \ldots, \boldsymbol{\nu}^{(K)}\right]$ are the optimization variables, $c^{(i)}$ is the cluster in which the ith training sample is assigned to, and $\boldsymbol{\nu}^{(k)}$ is the vector of the kth centroid. To minimize the cost, the K-means algorithm employs alternating optimization as summarized in Algorithm 1.

Specifically, given the training set $\mathcal{M}$ and hyperparameter K, the algorithm randomly chooses K samples as the initial centroids. For example, as in [91] the training set could

Algorithm 1 K-Means Algorithm

Input: $\mathcal{M}, K$
Output: $\boldsymbol{c}, \boldsymbol{N}$
Initialize $\boldsymbol{N}$ by randomly assigning $\boldsymbol{v}^{(k)} = \boldsymbol{x}^{(i)}$, where $k = \{1, \ldots, K\}$ and $i = \{1, \ldots, M\}$
Until convergence
For $i = 1$ to M
    Assign $c^{(i)}$ using (18)
For $k = 1$ to K
    Compute $\boldsymbol{v}^{(k)}$ using (19)

be the user coordinates and the hyperparameter could be the user groups. Then, the training samples are associated with one of these centroids as follows:

$$c^{(i)} = \arg\min_{k} \left\| \boldsymbol{x}^{(i)} - \boldsymbol{v}^{(k)} \right\|^2 . \tag{18}$$

When all the samples have been associated to a centroid, the algorithm then computes the vector of the new centroids as follows:

$$\boldsymbol{v}^{(k)} = \frac{\sum_{i=1}^{M} 1\left(c^{(i)} = k\right) \boldsymbol{x}^{(i)}}{\sum_{i=1}^{M} 1\left(c^{(i)} = k\right)}, \tag{19}$$

where $1(\cdot)$ is an indicator function. By optimizing these variables alternately, the variables will gradually converge to an optimal solution. Given the optimal variables $\boldsymbol{c}$ and $\boldsymbol{N}$, the K-means algorithm may then identify the implicit properties of the input.

Another algorithm is PCA. This algorithm reduces high dimensional data into low dimensional data by finding the basis onto which the data can be projected onto while minimizing the error. It is can be used to either compress data or interpret high dimensional data in a lower dimension. Thus, in mMIMO, it is suitable for applications such as compressing the CSI feedback [92] or reducing the features of a DNN [93]. For ease of exposition, let us denote $\bar{\boldsymbol{X}}$ as the mean normalized matrix of the input matrix $\boldsymbol{X} = \left[\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(M)}\right]$ (e.g., channel vectors of T update time) and $\boldsymbol{\Sigma} = \frac{1}{M} XX^H$ as the normalized covariance matrix which is a positive semidefinite matrix. Using singular value decomposition (SVD), the covariance matrix can be rewritten as follows:

$$\boldsymbol{\Sigma} = \boldsymbol{V}\boldsymbol{\Lambda}\boldsymbol{V}^H, \tag{20}$$

where $\boldsymbol{V}$ is a unitary matrix and $\boldsymbol{\Lambda}$ is a diagonal matrix whose values are in descending order. Denote the first kth column of the $\boldsymbol{V}$ as the compression matrix $\boldsymbol{Z}$, i.e., $\boldsymbol{Z} = [\boldsymbol{v}^{(1)}, \ldots, \boldsymbol{v}^{(k)}]$. We can then obtain the compressed CSI as follows:

$$\tilde{\boldsymbol{x}} = \boldsymbol{Z}^H \bar{\boldsymbol{x}}. \tag{21}$$

Similarly, $\boldsymbol{Z}$ can be used to reconstruct the approximated CSI in high dimension with some loss of information as follows:

$$\hat{\boldsymbol{x}} = \boldsymbol{Z}\tilde{\boldsymbol{x}}. \tag{22}$$

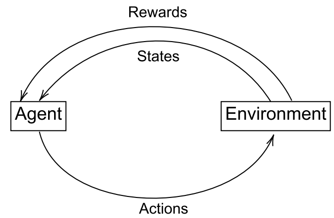

FIGURE 6. Reinforcement learning framework.

C. REINFORCEMENT LEARNING

Different from supervised and unsupervised learning, RL is not instructed on which actions to take. Instead, it allows its algorithm to interact with the environment via feedback. By performing a series of actions and continually leveraging the interaction, the algorithm learns over time which action actually maximizes its reward. Thus, RL is suitable for efficient power control and resource allocation in mMIMO.

As depicted in Fig. 6, RL consists of two major entities: the agent and the environment. The agent is responsible for taking appropriate actions and learning from the environment over time so as to maximize its cumulative reward. There are three important elements in a reinforcement learning system, namely states, actions, and rewards.

Mathematically, a reinforcement learning problem can be formulated using a Markov Decision Process (MDP). The MDP consists of:

1) a set of possible states, $\mathcal{S}$,
2) a set of possible actions, $\mathcal{A}$,
3) a set of set of transition probabilities, $\mathcal{P}$, where $\mathbb{P}\left(s^{\langle t+1\rangle}|s^{\langle t\rangle}, a^{\langle t\rangle}\right)$ is the probability that action $a^{\langle t\rangle}$ and $s^{\langle t\rangle}$ leads to $s^{\langle t+1\rangle}$,
4) a set of rewards, $\mathcal{R}$, where $\mathbb{E}\left[R^{\langle t\rangle}|s^{\langle t\rangle} = s, a^{\langle t\rangle} = a\right]$ is the expected reward when the state is $s^{\langle t\rangle}$ and the action is $a^{\langle t\rangle}$.

Each experience at time t can be represented by a tuple $e^{\langle t\rangle} = \left(s^{\langle t\rangle}, a^{\langle t\rangle}, R^{\langle t\rangle}, s^{\langle t+1\rangle}\right)$. For example, in mMIMO system, the state can be the signal-to-interference-and-noise-ratio (SINR), the action can be the power allocation, and the reward can be the overall spectral efficiency.

The discounted total long-term reward can be further formulated as follows:

$$G^{\langle t\rangle} = \sum_{m=0}^{M} \gamma^m R^{\langle t+m\rangle}, \tag{23}$$

where $0 < \gamma < 1$ is the discount rate and M is the final time step whose value might be finite (e.g., episodic tasks) or infinite (e.g., continuing task).

In reinforcement learning, there are two important functions: state-value function and action-value function. The state-value function estimates the long-term reward where the agent is in state s and follows a policy π. The state-value function is defined as follows:

$$\upsilon_\pi(s) = \mathbb{E}\left[G^{\langle t\rangle}|s^{\langle t\rangle} = s\right]. \tag{24}$$

The action-value function (also known as Q-function) is a function that estimates the long-term reward where the agent is in state s and executes an action a. More formally, the Q-function is defined as follows:

$$Q_\pi (s, a) = \mathbb{E}\left[G^{\langle t\rangle} | s^{\langle t\rangle} = s, a^{\langle t\rangle} = a\right]. \quad (25)$$

Having these functions, the agent requires a policy $\pi (s, a)$ to infer the action at the state s. This policy can be described as follows:

$$\pi (s, a) = \mathbb{P}\left(s^{\langle t\rangle} = s, a^{\langle t\rangle} = a\right). \quad (26)$$

The objective of reinforcement learning is to solve the MDP problem. The MDP problem is equivalent to finding the optimal policy that maximizes the long-term reward which can be formulated as follows:

$$\upsilon^* (s) = \max_\pi \upsilon_\pi (s), \forall s. \quad (27)$$

To optimize the state-value function, the principle of optimality states that the value of a state under an optimal policy π must be equal to the expected return for the best action from that state. Following this principle, the optimal state-value can be rewritten as follows:

$$\upsilon^* (s) = \max_a Q (s, a), \forall s, a. \quad (28)$$

Using (27)-(28), the optimal condition can be derived using the Bellman's optimality equation which is defined as follows:

$$Q^* (s, a) = \mathbb{E}\left[R^{\langle t\rangle} + \gamma \max_{a'} Q^*\left(s^{\langle t+1\rangle}, a'\right) | s^{\langle t\rangle} = s, a^{\langle t\rangle} = a\right]. \quad (29)$$

As seen in (29), the MDP problem can be efficiently solved if the complete knowledge (e.g., the transition probabilities and rewards) of the MDP are known. Nevertheless, in practice, it is difficult to obtain complete knowledge of the MDP. To address this issue, there are two commonly used methods, namely value-learning method such as deep Q-network (DQN) [94], and the policy-learning method such as deterministic deep policy gradient (DDPG) [8].

The former aims to learn the Q-function. Specifically, given the previous state-action pairs as training samples, the DQN aims to approximate $Q (s, a)$ with $\hat{Q} (s, a, \boldsymbol{w})$ using DNN. The $\hat{Q} (s, a, \boldsymbol{w})$ is a nonlinear function parameterized by $\boldsymbol{w}$ where the cost function of the DNN can be formulated as follows:

$$J (\boldsymbol{w}) = \mathbb{E}\left[\left\| \left(R^{\langle t\rangle} + \gamma \max_{a'} \hat{Q}\left(s', a', \boldsymbol{w}'\right)\right) - \hat{Q} (s, a, \boldsymbol{w})\right\|^2\right], \quad (30)$$

Meanwhile, the gradient of J can be derived as follows:

$$D_{\boldsymbol{w}} = \mathbb{E}\left[\left(\left(R^{\langle t\rangle} + \gamma \max_{a'} \hat{Q}\left(s', a', \boldsymbol{w}'\right)\right) - \hat{Q} (s, a, \boldsymbol{w})\right) \nabla_{\boldsymbol{w}} \hat{Q} (s, a, \boldsymbol{w})\right] \quad (31)$$

Using (30) and (31), the DNN provides $\hat{Q} (s, a, \boldsymbol{w})$ for all possible (s, a) pairs. The DQN then chooses the action a' based on an epsilon-greedy policy that provides the highest Q-function. Finally, the environment provides the actual reward and actual next state, which is further utilized in the DNN. The algorithm then repeatedly trains, approximates, makes decisions, and observes the state to ultimately maximize its long-term reward.

DQN is a powerful method, however, it is still not a suitable approach if the environment is highly stochastic or when the action space is large or continuous. To address this drawback, an alternative is to employ the DDPG. DDPG consists of four networks: an actor network, a critic network, a target actor network, and a target critic network.

To achieve exploration, the policy of DDPG can be defined by adding noise as follows:

$$a (s) = \mu\left(s, \boldsymbol{w}_{\boldsymbol{\mu}}\right) + \boldsymbol{\phi}, \quad (32)$$

where s is the input of the actor network, $\boldsymbol{w}_{\boldsymbol{\mu}}$ is the weight of the actor network, $\mu\left(s, \boldsymbol{w}_{\boldsymbol{\mu}}\right)$ is the output of the actor network (which is an action), and $\boldsymbol{\phi}$ is the exploration noise. The actor network is trained by maximizing the state-value function and the cost function can be formulated as follows:

$$J\left(\boldsymbol{w}_{\boldsymbol{\mu}}\right) = Q\left(s, a = \mu\left(s, \boldsymbol{w}_{\boldsymbol{\mu}}\right), \boldsymbol{w}_{\boldsymbol{c}}\right), \quad (33)$$

where $\boldsymbol{w}_{\boldsymbol{c}}$ is the weight of the critic network. Under the assumption that the state-value function is differentiable, the parameters of the actor network can be updated via gradient descent. In particular, the gradient can be computed as follows:

$$D_{\boldsymbol{w}_{\boldsymbol{\mu}}} = \nabla_a Q\left(s, a, \boldsymbol{w}_{\boldsymbol{c}}\right) \nabla_{\boldsymbol{w}_{\boldsymbol{\mu}}} \mu\left(s, \boldsymbol{w}_{\boldsymbol{\mu}}\right). \quad (34)$$

The output of the actor network is used as the input of the critic network and $\boldsymbol{w}_{\boldsymbol{\mu}}$ is updated by maximizing the output of the critic network and fixing the weight of the critic network. A target value for the state-value function can be obtained as follows:

$$q = R^{\langle t\rangle} + \gamma Q_{\text{target}}\left(s^{\langle t+1\rangle}, a_{\text{target}}, \boldsymbol{w}_{c_{\text{target}}}\right), \quad (35)$$

where $Q_{\text{target}}\left(s^{\langle t+1\rangle}, a_{\text{target}}, \boldsymbol{w}_{c_{\text{target}}}\right)$ is the output of the target critic network, $\boldsymbol{w}_{c_{\text{target}}}$ is the weight of the target critic network, $a_{\text{target}} = \mu_{\text{target}}\left(s^{\langle t+1\rangle}, \boldsymbol{w}_{\mu_{\text{target}}}\right)$ is the output of the target actor network, and $\boldsymbol{w}_{\mu_{\text{target}}}$ is the weight of the target actor network. Note that the output of the target actor network is similarly used as the input of the target critic network. The critic network can then be updated by minimizing the loss function as follows:

$$\mathcal{L} = \left(q - Q\left(s, a, \boldsymbol{w}_{\boldsymbol{c}}\right)\right)^2. \quad (36)$$

Meanwhile, weights of the target actor and target critic networks are updated as follows:

$$\begin{aligned} \boldsymbol{w}_{\mu_{\text{target}}} &\leftarrow \tau \boldsymbol{w}_\mu + (1-\tau) \boldsymbol{w}_{\mu_{\text{target}}}, \\ \boldsymbol{w}_{c_{\text{target}}} &\leftarrow \tau \boldsymbol{w}_c + (1-\tau) \boldsymbol{w}_{c_{\text{target}}}, \end{aligned} \quad (37)$$

where τ is the soft updating parameter. In addition, each experience e^t is stored in the replay buffer where fixed number of experience is randomly selected for network updates. For an example, interested reader may refer to [95] where both DQN- and DDPG-power allocation are proposed for CF-mMIMO.

V. DEPLOYMENT OF I-mMIMO SYSTEMS

In this section, we provide an answer to RQ1 by discussing the deployment strategies for the I-mMIMO systems. These include federated learning, the training approach, testbed and experimental platform, and efforts toward standardization.

A. FEDERATED LEARNING

Federated learning (FL) has been proposed for the deployment of ML in wireless communication systems in order to overcome the constraints of high latency and address data privacy concerns in a centralized network structure [96]. In the federated learning framework, it is assumed that there is a set of UTs K where each UT has some local training samples, m_k. To perform the training, the centralized server will select a random fraction of UTs (e.g., $\kappa \leq 1$) and send the current global state to each of these UTs. Each selected UT will then perform local computation based on the global state and its local training samples. Upon completion, the selected UTs will send their local updates to the server and the server will apply these updates to its global state and repeat the process until convergence.

Mathematically, the cost function in a federated learning framework (e.g., a supervised learning problem) can be formulated as follows:

$$J_{\mathrm{FL}}\left(\tilde{\boldsymbol{w}}\right) = \sum_{k=1}^{K} \frac{m_k}{M} \mathcal{L}_k\left(\tilde{\boldsymbol{w}}\right), \tag{38}$$

where $\mathcal{L}_k\left(\tilde{\boldsymbol{w}}\right) = \frac{1}{m_k}\sum_{i=1}^{m_k} \mathcal{L}\left(\hat{y}_k^{(i)}, y_k^{(i)}\right)$ is the loss function of client $k \in \{1, \ldots, K\}$. The cost function (38) can be minimized via several algorithms. One of the state-of-the-art algorithms is the federated averaging. In federated averaging, each client locally compute its loss function, $\mathcal{L}_k\left(\tilde{\boldsymbol{w}}\right)$, and updates its parameters, $\tilde{\boldsymbol{w}}_k$, as follows:

$$\tilde{\boldsymbol{w}}_k := \tilde{\boldsymbol{w}}_k - \alpha \frac{\partial \mathcal{L}_k}{\partial \tilde{\boldsymbol{w}}_k}. \tag{39}$$

Meanwhile, the centralized server updates the global state, $\tilde{\boldsymbol{w}}$, as follows:

$$\tilde{\boldsymbol{w}} := \tilde{\boldsymbol{w}} - \sum_{k=1}^{K} \frac{m_k}{M} \tilde{\boldsymbol{w}}_k. \tag{40}$$

The federated averaging algorithm is presented in Algorithm 2. It is worth noting that one can increase the client computation by iterating the local update in (39) several times before computing the averaging step in (40). Specifically, [97] shows that once a minimum level of parallelism is attained among the clients, adding more computation to each client actually improves the training performance.

Algorithm 2 Federated Averaging Algorithm

Until convergence
Server executes
  Input: $\alpha, \tilde{\boldsymbol{w}}_k$ for $k = 1, \ldots, K$
  Output: $\tilde{\boldsymbol{w}}$
  S := Select a random fraction of max $(\kappa \cdot K, 1)$clients
  For each client in S **parallel do**
    ClientUpdate($\tilde{\boldsymbol{w}}$,S)
  Update the parameters $\tilde{\boldsymbol{w}}$ as follows:
  $\tilde{\boldsymbol{w}} := \tilde{\boldsymbol{w}} - \sum_{k=1}^{K} \frac{m_k}{M} \tilde{\boldsymbol{w}}_k.$
ClientUpdate($\tilde{\boldsymbol{w}}$,S)
  Input: $\alpha, \tilde{\boldsymbol{w}}, \boldsymbol{X}_k, \boldsymbol{Y}_k$
  Output: $\tilde{\boldsymbol{w}}_k$
    Perform ML task and compute the lost function $\mathcal{L}_k\left(\tilde{\boldsymbol{w}}\right)$
    Update the parameters $\tilde{\boldsymbol{w}}_k$ as follows:
    $\tilde{\boldsymbol{w}}_k := \tilde{\boldsymbol{w}}_k - \alpha \frac{\partial \mathcal{L}_k}{\partial \tilde{\boldsymbol{w}}_k},$

In more advanced cases, federated learning can be further extended to vertical federated learning, horizontal federated learning, and federated transfer learning. In vertical federated learning, the overall training set might share the same client space but differ in feature space. In horizontal federated learning, the training set might share the same feature space but a different client space. In addition, the overall training set in federated transfer learning might have distinctions in both client space and feature space. To address this gap, a common representation between the two spaces must be learned by using the common training samples and applied prediction to samples with a single-sided space. From the above, it is clear that federated learning is ideal for problems that require personalized data from devices, data that is private or massive in size, and labels that can be directly obtained from the clients. Nevertheless, due to the decentralized nature, FL is also challenged by highly dynamic data, correlated data, security issues, inference attacks, failures, and unresponsive updates [97], [98], [99]. Moreover, the cost of communications dominates the cost of computations in FL and this motivates the applications in I-mMIMO systems [100], [101], [102], [103], [104], [105]. The use of FL was shown to reduce the transmission overhead in [106] and [103], improved the channel estimation performance, and faster computation in [100] and [101].

B. TRAINING APPROACH

In addition to different categories of ML techniques, the training approach is another important aspect that needs to be considered. The ML training approach in I-mMIMO can be classified into offline, online [107], [108], [109], [110], [111] and offline-online [112]. In the offline training approach, training of the ML model is based on historical data, while in the online, real-time data are explored for both training and decision making. The offline-online is a two-step approach

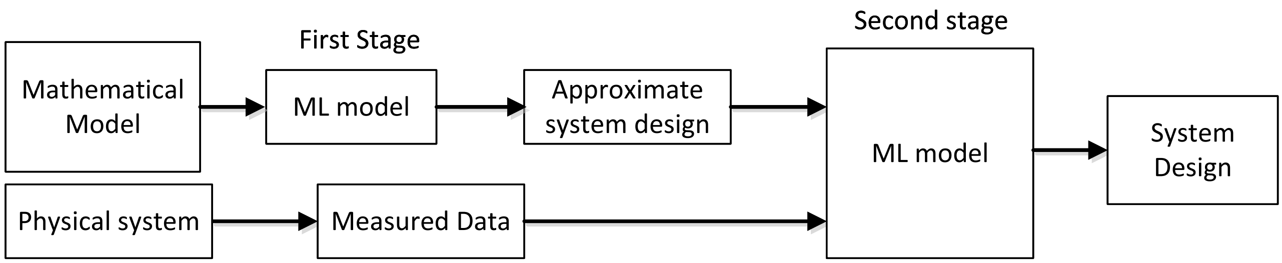

FIGURE 7. Two-step training approach for I-mMIMO systems.

that combines offline training with online training in order to reduce training time, improve training stability, and improve the prediction based on changes in input parameters. Furthermore, the training approach can either use a model-driven DL approach or a data-driven DL approach [113].

The data-driven approach is based on the conventional use of ANN as a black box for training a large amount of data. This approach is considered time-consuming and requires a large data set which is not suitable for practical wireless communication. On the other hand, the model-driven DL exploits the existing wireless communication mathematical models and algorithms to develop a deep network. Hence, it optimizes the parameters or adds some parameters learned by DL in the existing model. While this makes it require less training data, training time and enables rapid implementation it can be prone to error if the underlying mathematical model is inaccurate. To address this, Zappone *et al.* [22] proposed a two-step approach where the ANN is trained using data from a theoretical model or expert knowledge domain, and the ANN is later fine-tuned using an empirical or sizable measured data set. The illustration of the two-step approach is shown in Fig. 7. In terms of application, a large number of research works have investigated the application of ML in different blocks of the mMIMO communication systems. A few research works have also considered the application of ML in end-to-end communication systems [114], [115]. In end-to-end communication, suitable ML models and system requirements that can guarantee acceptable I-mMIMO system performance need to be considered.

C. TESTBED AND EXPERIMENTAL PLATFORMS

The development of testbeds for I-mMIMO system plays a vital role in its realization. Examples of testbeds for 5G and B5G communication networks are CTTC 5G end-to-end experimental platform and true-data testbed for 5G/B5G intelligent network (TTIN) [116], [117]. The CTTC 5G end-to-end experimental platform that integrates different testbeds such as ADRENALINE and EXTREME, and GEDOMIS was proposed for testing advanced end-to-end internet of things (IoT) and mobile services [115]. On the other hand, the TTIN is an open-source platform that aims to integrate network data collection, dataset production, intelligent data analysis, and in-situ inspection of AI algorithms for 5G I-mMIMO systems. This includes support for the application of DL techniques on measured data and model-based data. The limitation of these existing platforms is that they are configured for a defined parameter that may not support emerging I-mMIMO scenarios for optimal network management. In addition, the integration of network infrastructure for real-time applications may present a bottleneck to intending users due to technical challenges. Hence, AI-enabled Massive MIMO (AIMM) [118] an initiative of the European collaborative research and development project aims to develop and deploy testbeds powered by AI and ML for B5G radio access networks.

D. DATASET

The methods for dataset generation include the use of simulation and measurement campaigns. In the simulated method, data can be generated by applying ray-tracing methods for channel realization and the optimization problem is solved computationally. The results from the computation are used as label data in a supervised learning application. The use of datasets has been advocated for the performance evaluation of I-mMIMO systems [90], [119], [120]. These enable benchmarking, and comparison of the different ML algorithm and promotes reproducibility. For instance, [90] presents a dataset for the mmWave mMIMO channel that characterizes the environment of the UTs and BS. A method for generating a dataset for mmWave mMIMO channel realization using ray-tracing and vehicle traffic simulators was proposed in [119]. Measured datasets for mMIMO channels with 64 antenna systems are made available in [120] and [121].

E. STANDARDIZATION

Standard organizations such as the 3GPP and International Telecommunication Union (ITU) have started consultation in order to define a framework for the application of ML in radio access networks. Examples are the 3GPP [122] and International Telecommunication Union (ITU) [123], [124]. The focus of the 3GPP framework is on the implementation of ML for self-organizing networks (SON) functionality in the 5G NG radio access network (NG-RAN). On the other hand, the ITU aims to develop an architectural framework that enables the integration of ML functionalities in the IMT-2020 and future networks [123], [124]. The ITU has proposed three level architectural components which are: an ML pipeline, ML function orchestrator, and ML sandbox to manage ML functionalities and communication networks.

VI. REVIEW OF APPLICATIONS OF ML IN mMIMO

In this section, the review of literature on the application of ML in mMIMO systems is presented to provide answers to RQ2: What is the current research trend in the application of ML in I-mMIMO systems? The application of ML is discussed in different areas: intelligent reflective surfaces, user localization, spectral and energy efficiency, modulation and decoding, low-bit ADC systems, I-mMIMO decoder, intelligent CF-mMIMO, and channel estimation and beamforming.

A. INTELLIGENT REFLECTIVE SURFACES

Intelligent reflecting surface (IRS), also known as reflecting intelligent surface (RIS) or large intelligent surface (LIS), is a low cost meta-material surface consisting of a large number of passive reflecting elements. Each of the passive reflecting elements is capable of manipulating the amplitude and phase of the impinging signal. By smartly configuring these elements, the received signal strength/interference can be enhanced/mitigated. Therefore, IRS has the capability to improve the overall network performance at low cost. Nevertheless, the advantage of IRS highly relies on the accuracy of the CSI. But CSI acquisition in an IRS-assisted mMIMO system remains a challenging task. This is because the BS-UT link through the IRS is a cascaded channel. The passive features of the IRS also introduce challenges to estimate the IRS-BS and IRS-UT channels. Thus, several works have employed DL to address the CSI acquisition problems. For instance, [125] proposes a twin CNN for the estimation of direct and cascaded channels. The CNNs are fed with the (direct/cascaded) received pilot signals to construct a non-linear relationship. The trained CNN is then used to estimate the direct and cascaded channels. In [125], the authors show that the proposed twin CNN is robust to corrupted data, e.g., AoA mismatch up to 4 degrees and non-ideal switching of LIS elements. In [126], a hybrid passive/active IRS architecture is considered. Based on this architecture, the authors in [126] suggest to employing compressive sensing for CE whilst complex valued denoising CNN (CV-DnCNN) is proposed to further improve the estimation performance. Interestingly, they show that their DL solution can work efficiently under various SNR and number of multipath components even if the solution is trained at other SNR or number of multipath components. To reduce the pilot overhead, [127] considers partially activated RIS elements and proposes a three-stage CSI acquisition. In the first stage, the direct channel is estimated via DNN followed by active RIS elements via CNN in the second stage. Then, inactive RIS elements are predicted via DNN. Interestingly, the three-stage CSI acquisition solution provides good performance over different pilot overhead ratios.

In addition, DL can also be used to obtain optimal IRS configuration. For example, [128] proposes a DL scheme for the online configuration of RIS in indoor communication environments. Specifically, the proposed scheme leverages a database of coordinated fingerprints during the offline training phase. The fingerprint database is used to train the weight and bias of a DNN, which maps the measured coordinates to an optimal configuration. During the online phase, the user estimates its position and feeds the information to the DNN at the RIS. The RIS then uses the optimal phase configuration to enhance the overall throughput. In addition, [129] considers LIS architecture where a few elements are active and the other elements are passive. Then, a DNN is proposed for the LIS to learn the optimal reflecting beamforming vector. The authors show that with a small amount of active IRS elements DL solution can still approach the upper bound which assumes perfect channel knowledge.

B. USER LOCALIZATION

The conventional methods such as geometry-based and fingerprint-based positioning methods have exploited propagation parameters such as channel impulse response, propagation delay, AoA, or RSS to localize UTs. However, these methods are prone to positioning performance degradation due to non-line-of-sight (NLoS) propagation, and higher computational complexity. To address these challenges, several ML approaches have been investigated in the literature [13], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139] to learn a function that maps the input propagation parameters to the UT position. The fingerprint-based positioning method using CNN in a co-located mMIMO system was presented in [13]. A framework that jointly extracts and processes channel information generated by COST 2100 channel model showed promising results in the use of CNN for localization. To reduce the training time for the fingerprint-based ML method, a two-step approach was proposed in [130]. The first step involves training based on the simulation model and the second phase involves fine-tuning the trained model obtained in the first step with a small number of measured data. The result showed a significant amount of reduction in training samples. Another approach to reduce sample and training time called triplet network was proposed in [135]. The proposed method attempts to exploit a low-dimensional representation of the CSI by using three branches of deep feed-forward networks. The result shows good accuracy with less amount of CSI information compared to the neural network.

Angle-delay channel power matrix (ADCPM) which comprises of stationary multi-path characteristics was exploited for UT positioning in co-located mMIMO system in [138]. A three-dimensional (3D) CNN was proposed to localize the position of the UTs where the ADCPM was used as input. The result shows higher positioning accuracy with reduced computational complexity and robustness to noise contamination of the fingerprints. The RSS was exploited in [134] and [139] to localize UTs in a DAS mMIMO system by using the Gaussian process (GP) regression ML technique. Due to the limitation of the GP a numerical approximation GP that improves the estimation of UT locations was proposed in [134] but does not account for noise due to shadowing. Hence, a new Gaussian process regression method called reconstruction-cum-Gaussian approximation GP (RecGaGP) that accounts for noise due to shadowing was explored in [139] to estimate the UT's locations from their respective RSS vectors in a DAS mMIMO systems. In [136] De Bast and Pollin investigated the accuracy of the CSI-based localization systems using CNN in line-of-sight (LoS) and NLoS scenarios. Their finding shows that the performance of the CNN CSI-based localization is influenced by the topology of the environment in an in-door scenario due to the multi-path components of the channel. The use of extreme learning machine (ELM) for CSI-based localization of UTs was explored in [140]. The study from [140] shows that the number of BS antennas can influence the localization accuracy, especially for BS antennas with $M \leq 8$.

While some of these works show some promising simulation results in terms of the application of DL techniques, practical implementation is still an open issue. Several factors such as colored noise, hardware impairments, topology and change of environment, and periodic updates of the training model need to be considered [136], [139]. A summary of some of the applications of ML for user localization is presented in Table 3.

C. SPECTRAL AND ENERGY EFFICIENCY

The aim of mMIMO is to maximize throughput performance with low power consumption by considering different factors such as transmission power and circuit power expenditure. To achieve this, several approaches have been considered in the literature. These approaches include AS, power control to minimize interference, low complexity algorithms, optimal resource allocations [141] and spectral efficiency prediction [142]. The ML that has been exploited in overcoming some of the challenges in the CM-MIMO systems and promoting I-mMIMO systems are discussed under the following: power control, resource allocation, and AS.

1) POWER CONTROL

ML techniques have been applied in intelligent power control in mMIMO systems under different approaches [143], [144], [145], [146], [147], [148], [149]. In [149] and [143], deep CNN was used to predict the data and pilot power based on large-scale fading coefficients in order to achieve maximum sum spectral efficiency. Similarly, in [144], [147], and [148], the geographical location information of the UTs was exploited for power control based on distance-dependent path loss. The results from these works show the ability to use ML techniques to achieve near-optimum performance without necessarily performing complex channel estimation. This reduces the processing time to determine the optimal power allocation of each UT when compared to the standard optimization approach. However, majority of these studies are based on supervised ML techniques.

2) RESOURCE ALLOCATION

The application of ML has been explored for intelligent resource allocation in order to improve spectral efficiency for the B5G networks [150], [151]. The use of ML has been shown to overcome the computational complexity related to the model-based approach in CM-MIMO systems [57]. The optimal solution for sum-rate maximization has been obtained by using DL in the scheduling of UTs and link resources [57], [151], [152], [153], [154]. Computational complexity reduction has been achieved by exploiting geographical location instead of CSI [151]. Furthermore, ML has been proposed for an optimal pilot allocation scheme in order to reduce the computational complexity associated with heuristic algorithms and optimization theory in mMIMO systems [155], [156] and joint scheduling with DL-based beamforming in [157].

3) ANTENNA SELECTION

The use of ML is being employed to solve the challenges faced in the procurement of optimal antenna subsets, especially in mMIMO systems. The aim of optimal selection of antenna is to reduce the computational complexity while maintaining a good signal-to-noise ratio (SNR) and maximizing channel capacity. ML has been proposed for AS as a decision-making or classification problem in place of optimization and greedy search for subarray selection. Studies on AS using ML have been presented in [158], [159], [160], [161], [162], [163], [164], [165], and [166]. In [166], a comparison of ML and model-driven techniques for AS was presented. The support vector machine (SVM) and k-nearest neighbor (k-NN) classifier were used to predict the optimal antenna subset for a new channel with the SVM showing a better communication performance over the k-NN. Following the outcome in [166], Cai *et al.* [158], compared the CNN with the k-NN and SVM in the selection of optimal receive antenna subset based on simulated channel matrix between transmit and receive antennas. The result shows better performance using CNN when compared with k-NN and SVM. In [161], a self-supervised learning approach using monte Carlo tree search (MCTS) and linear regression for AS was proposed. The use of ML was proposed for joint AS and hybrid-beamforming using the CNN framework in [162] and [165]. Elbir and Mishra [162], [165] showed that the proposed method showed high accuracy, time reduction, and improved spectral efficiency over conventional AS algorithms. While the majority of the works have focused on theoretical analysis, some works have carried out hardware implementation of ML for AS. For example, Zhong *et al.* demonstrated the use of DNN for AS by implementing a DL AS MIMO aided software defined radio (SDR) system [160] and the use of k-NN for AS in a real-time system was presented in [163]. The use of DNN for AS was considered in [164] in order to effectively extrapolate downlink channels from the partial uplink channels. Better extrapolation performance was observed when compared to the uniform AS scheme. A summary of some of the different approaches in

TABLE 3. Summary of application of ML for user localization.

Ref	mMIMO technique	Approach	Validation
[138]	Co-located	3D CNN	Simulation
[139]	DAS	RSSI-based localization using GP	Simulation
[136]	Co-located	CSI-based localization using CNN	Experimental
[134]	DAS	RSSI-based localization using GP and numerical approximation GP (NaGP)	Simulation
[140]	Co-located	CSI-based localization using the ELM	Experimental
[13]	Co-located	CSI-based localization using CNN	Simulation
[130]	Co-located	CSI-based localization using ANN	Simulated and measured data points
[137]	Co-located	Nadaraya-Watson estimator for similarity-based prediction	Simulation
[135]	Co-located	CSI-based localization using triplet network three branches of ANN	Simulation

application of ML for spectral and energy efficiency in the I-mMIMO systems is presented in Table 4.

4) SUMMARY

While the application of ML in AS, power control, and resource control helps to improve and maximize spectral efficiency in the mMIMO systems, the application of ML to predict spectral efficiency using ML techniques is another approach. In [142], different ML techniques were explored in the prediction of average spectral efficiency and user spectral efficiency achievable with precoding methods for the mMIMO systems. The challenge with this approach is that it requires feature extraction based on the existing mMIMO systems configuration and systems performance metrics like the SINR. More research studies are needed in the prediction of spectral efficiency based on usage patterns and mMIMO systems performance.

D. MODULATION AND CODING

Adaptive modulation and coding is a form of link adaptation process that involves matching the coding and modulation to the radio link. Some of the modulation schemes include binary frequency-shift keying (BFSK), differential quadrature phase-shift keying (DQPSK), 16 quadrature amplitude modulation (16QAM), quaternary pulse amplitude modulation (4PAM), minimum shift keying (MSK), Gaussian minimum shift keying (GMSK), quadrature phase shift keying (QPSK), and eight phase-shift keying (8PSK).

The radio link is dynamic due to the susceptibility to the effect of pathloss, interference, noise, environmental factors, and non-linearities. Hence, automatic modulation classification (ACM) or automatic modulation recognition (AMR) are being employed to identify the appropriate modulation scheme used to modulate an unknown signal without priori knowledge or human input [170]. The ACM/AMR involves signal pre-processing and signal classification. Two main modulation classifications identified in [171] are likelihood-based and feature-based. These two methods are summarized in Table 5.

To address the limitation of the conventional methods i.e. the likelihood and feature-based methods identified in Table 5, different DL approaches have been proposed in [172], [173], [174], [175], [176], [177], and [171] to meet the need of mMIMO systems. In [173], the CNN and RNN DL methods were used to classify 6 modulation signals which are BFSK, DQPSK, 16QAM, 4PAM, MSK, and GMSK over additive white Gaussian noise (AWGN) channel and Rayleigh fading channel, respectively. The results from the study show better AMR performance with less complex feature extraction than the conventional method. Contrary to the approach in [173] which did not consider the presence of phase-offset (PO) in the DL-AMR approach [176] investigated the effect of PO in orthogonal frequency division multiplexing (OFDM) systems. The result from [176] shows that while CNN is robust and outperforms the conventional feature-based methods, the accuracy degrades at low SNR in the presence of PO for BPSK, QPSK, 8PSK, and 16QAM OFDM systems.

E. REDUCTION OF HARDWARE COMPLEXITY

The use of low-bit ADCs in mMIMO systems is advocated due to the low hardware complexity (i.e eliminates the need for an automatic gain controller) and reduction in power consumption from continuous-amplitude sampling and quantization [178]. Despite the benefits, low-resolution ADCs present a number of technical difficulties in mMIMO detection and channel estimation. Hence, the use of ML has been explored in low-bit ADC mMIMO systems [179], [180], [181]. For instance, the application of a Feedforward NN-based bit allocation scheme was proposed to determine the bit allocation that offers optimal energy efficiency [179], while a supervised learning approach was explored in a multi-hop relay and mMIMO BS to overcome the challenges of detection in a one-bit ADC transceiver [180]. Similar works have also explored the use of the ML approach in a low-bit ADC system [181], [182], [183].

Hardware complexity can also be reduced by limiting the number of RF chains in mMIMO systems via a hybrid architecture that employs hybrid beamforming (HBF) and

TABLE 4. Research summary of application of ML for spectral and energy efficiency.

Ref.	Focus	AI Techniques	Findings	Validation
Van Chien et al. [149]	Power control and prediction of transmit power in an uplink multicell mMIMO system with fixed BS location and dynamic user locations	CNN	Achieved below 1 ms run-time for power prediction	Theoretical concept and numerical analysis
Zhou et al. [150]	Prediction and assignment of resource allocation to UTs	LSTM	Proactive prediction lowers packet loss rate and increased throughput	Theoretical concept and simulation
Sanguinetti et al. [144]	Power allocation in a downlink mMIMO based on UT's geographical location	Feedforward neural network	Reduced computational complexity with near-optimal performance	Theoretical concept and numerical analysis
Zappone et al. [151]	User-cell association based on UT's geographical location	Deep Feedforward ANN	Reduced computational complexity in association rules	Theoretical concept and numerical analysis
Yang et al. [167]	Group alignment user scheduling scheme	RL	Enhanced capacity-coverage optimization	Theoretical concept and numerical analysis
Van Chien et al. [143]	Power control based on joint pilot and data power prediction	CNN	Increased spectral efficiency	Theoretical concept and numerical analysis
D'Andrea et al. [168]	Sum-rate-max and max-min power allocation in the uplink CF-mMIMO system	ANN	Performance affected shadowing effects	Theoretical concept and numerical analysis
Bashar et al. [145], [146]	Maximum sum rate power control in uplink limited Fronthaul CF-mMIMO system	Deep CNN	Large scale fading DL-based power control offers increased achievable uplink sum rate	Theoretical concept and numerical analysis
Zhang and Mao [147]	Power control scheme based on UT's geographical location	CNN and deep residual learning	Achieved near-optimal energy efficiency performance and suitable for different fading channels	Theoretical concept and numerical analysis
Cui et al. [57]	Link scheduling based on geographical location of interfering or interfered UTs in D2D network	DNN	Optimal network utility and fairness without CSI	Theoretical concept and numerical analysis
Bu and Jiang [152]	Scheduling of UTs and resource allocation scheme	Multi-agent RL	Higher learning rates results in higher sum-rate performance	Theoretical concept and simulation
Kim et al. [155]	Pilot allocation scheme based on UT distribution and geographical location	Deep multilayer perceptron (MLP)	High accuracy and normalized capacity gain	Theoretical concept and simulation
Shi et al. [154]	UT scheduling based on the ordered eigenvalues of hermitian matrices	ANN	Achieves optimal scheduling performance with reduced complexity	Theoretical concept and simulation
Yu et al. [153]	UTs scheduling with correlated Rician fading channels	CNN and deep residual learning	Achieves same performance as exhaustive search	Theoretical concept and simulation
Xu et al. [156]	Optimal pilot assignment scheme	Fully connected DNN	Improved MSE performance	Theoretical concept and simulation
Farsaei et al. [169]	Optimal selection of correlated UTs in LoS scenario	ANN	Reduced computational complexity and improved sum-rate	Theoretical concept, simulation and numerical analysis

hybrid combining (HBC) techniques. In Hybrid architecture, the radio frequency (RF) chains are much fewer than the mMIMO antennas and this opens up research issues in the area of complexity and performance in HBF, HBC, and channel estimation. To address these issues, the application of ML techniques was explored in [91], [175], [184], [185], [186], [187], [188], [189], [190], [191], [192], [193], [194], [195], [196], [197], [198], [199], [200], and [201]. ML techniques have been explored to address the complexity of predicting beamforming vectors and improving the robustness in hybrid precoders by taking account of imperfect channel matrices in [185], [186], [188], [190], [192], [193], [195], [197], [199],

TABLE 5. Classification modulation methods.

	Likelihood-based	Feature-based
Advantages	Optimal method and decrease the probability of misclassifications	No priori channel information required, makes use of signal processing, feature extraction for classification of modulated signal
Limitations	Detailed channel information and accurate channel parameter estimation is required, high computational complexity, poor performance from unknown channel conditions	Sub-optimal, requires the appropriate decision threshold, poor performance from unknown channel conditions

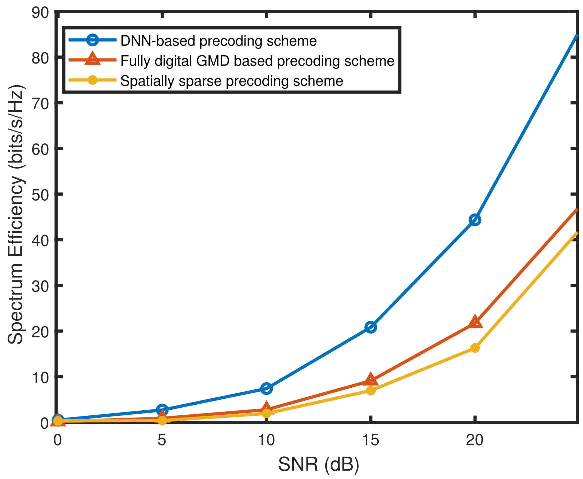

FIGURE 8. Improved spectral efficiency performance in ML-applied hybrid precoding [200].

and [201]. In addition, the ML approach has been applied to overcome the challenges of channel estimations and reduction of signal overhead feedbacks in [189], [191], [196], [198], and [200]. Other related works have also focused on applications of ML in HBC [186], [193]. Results from these works have shown an increase in spectral efficiency by leveraging the ability of ML techniques to learn the statistical structures in partial CSI feedback [199], [201], and exploiting the temporal correlation in time-varying channels [200]. An example of improved spectral efficiency performance in ML-applied hybrid precoding is shown in Fig. 8 [200]. The DNN-based precoding outperforms the classical approaches: geometric mean decomposition (GMD)-based scheme and the spatially sparse precoding scheme.

F. I-mMIMO DECODER

Several works have incorporated DL into the encoder/decoder to improve the network performance. For instance, [202] proposes a DeepCMC which consists of a fully-CNN autoencoder and residual layers at the decoder in conjunction with quantization and entropy coding blocks. A distributed DeepCMC which exploits the correlation among the CSI matrices of nearby users is also proposed in [202] to further reduce the overhead. Furthermore, a model-driven DL framework is proposed in [203] for both uplink and downlink communications. In addition, DL can also be integrated into the encoder/decoder for detection problems. For instance, [204] proposes a DLNet decoder to minimize the bit error rate. In [205], a concrete map detection (CMD) is proposed, which relaxes the probability mass function of the discrete random variable into a probability density function in a maximum a posterior detection problem. To further improve detection accuracy while limiting complexity, they also unfold the gradient descent algorithm into a DL-based model known as CMDNet. Moreover, a decoder that deals with a varying number of transmitters and is invariant to the order in which the users interact with the system can also be designed using DL [206].

G. INTELLIGENT CELL-FREE mMIMO SYSTEMS

In the CF-mMIMO systems, the signals are transmitted from the APs to the CPU using the fronthaul link. The signals from the APs are transmitted either by using the combine-quantize-and-forward (CQF) or quantize-and-forward (QF) to the CPU [145], [146]. This introduces the challenge of the limited capacity of the fronthaul links in a regime with massive numbers of APs. In addition, computational complexity and real-time constraints at the CPU where signals are combined and detected remain a challenge. To address some of these challenges, ML techniques have been employed in CF-mMIMO [145], [146], [168], [207], [208], [209], [210], [211], [212], [213]. In [207], an enhanced K-means clustering for a semi-blind CE approach was proposed to address the issues of fronthaul overhead and complexity. A DCNN combined with large-scale-fading in a limited fronthaul was used to determine optimal power control that maximizes the throughput while minimizing complexity [145]. Furthermore, the DL technique for power allocation was investigated in [213] and [168] to address the time constraint and computational complexity. The results from [213] and [168] have shown the DL techniques can achieve good approximation when compared with heuristic methods with lesser computation time and complexity.

H. CHANNEL ESTIMATION AND BEAMFORMING

The review of the application of ML in CE and beamforming in mMIMO systems has been discussed in detail in [60], [214], and [32]. Hence, we provide an overview by categorizing the studies into CE in FDD mMIMO and in TDD mMIMO systems.

1) CHANNEL ESTIMATION

The use of ML for intelligent CE in mMIMO systems helps to overcome the constraints faced in the complexity of finding accurate CSI with limited feedback. Studies on the application of ML approaches and methods have been presented in the literature [112], [202], [214], [215], [216], [217], [218], [219], [220], [221], [222], [223], [224], [225], [226], [227], [228], [229], [230], [231], [232], [233], [234], [235], [236], [237], [238], [239], [240], [241], [242], [243], [244],

[245], [246], [247], [248], [249], [250], [251], [252], [253], [254]. The majority of these studies have compared the ML approach with conventional CE such as maximum-likelihood, least-square estimation, and MMSE. ML techniques have been used to exploit the channel correlation, spatial and spectral correlation of CSI, bi-directional channel correlation, and temporal channel correlations in order to reduce the complexity and feedback needed in mMIMO systems [60].

In FDD mMIMO systems, pilot signals are sent to the UTs which estimate the CSI and feedback to the BS. This introduces overheads. The use of ML in mMIMO has been employed to address the limited feedback and bandwidth constraint in FDD systems. Hence different ML techniques and approaches have been proposed in the literature. Some of the approaches include the use of DL techniques for CSI feedback compression, quantization and recovery [112], [202], [215], [216], [217], [218], [219], [220], [221], [222], [223], [225], [226], [231], [234], [235], [237], [238], [240], [241], [243], [244], [245], [247], [248], [255], [256], [257], use of DL at the edge for CSI feedback [224], DL assisted blind CE [227], DL based CSI for maximal beamforming performance [228], ML clustering techniques design [229], [239], DL user grouping for joint spatial division and multiplexing (JSDM) [258], DL CSI prediction [21], [230], [232], [233], [246], DL with superimposed coding [236], [259], learning based remote channel inference [196], channel mapping to user position [137], [242], [260] and analog feedback [261], DL symbol level based CE [262].

In the TDD mMIMO systems the BS takes advantage of reciprocity to obtain CE using the uplink signal. This eliminates the feedback challenge. However, factors such as channel coherence time pose a challenge. The issue of channel aging and the effect of using low-bit ADC on channel estimation needs to be overcome. Hence, the use of ML has also been proposed for learning and prediction of UT's channel in the TDD mMIMO systems [250], [263], [264], [265], a blind multi-path classification in the uplink (UL) scheme [266] and the use of DL to estimate channels from quantized received signals in low-bit ADC system [19].

2) BEAMFORMING

The use of ML techniques has been investigated in I-mMIMO systems in order to focus a signal in the direction of the UTs. Examples include the application of ML in analog and digital beamforming mMIMO systems [192], [267], [268] and HBF in mmWave mMIMO systems [91], [175], [184], [185], [186], [187], [188], [189], [190], [191], [192], [193], [194], [195], [196], [197], [198], [199], [200], [201]. The key optimization problems addressed in I-mMIMO beamforming systems are to maximize sum-rate, power minimization, and SINR balancing while reducing computational complexity. To address this, supervised ML techniques such as k-NN, DNN, and SVM are used to predict the precoder [192], [199], [269] and precoder indicators such as AoA, [190], [270], [271]. Due to the challenge of obtaining the training labels, the use of unsupervised ML techniques for beamforming has been reported in [192] and [272]. The use of RL techniques for beamforming was reported in [273] and [274]. In [274], a deep RL algorithm that eliminates the need for CSI by jointly optimizing the power control, beamforming, and interference coordination were shown to outperform the fixed power allocation and exhaustive search algorithms in terms of time and obtaining an effective SINR required for beamforming gain. In [273], a Deep RL-based algorithm was proposed for HBF design known as PrecoderNet. The PrecoderNet was shown to adapt to changes in the environment under imperfect CSI and achieves higher spectral efficiency, BER, and time consumption compared to existing numerical hybrid beamformers and combiners algorithms.

I. SUMMARY

In summary, this literature review shows that ML has been investigated and explored in various aspects of the mMIMO systems. This includes different scenarios involving the operations and management of the PHY. It is interesting to note that a good number of research works have focused on the CE, especially in the FDD systems in an attempt to overcome the constraints of limited bandwidth and feedback. This is due to the important role CE plays in mMIMO systems. It is also important to note that traditional approaches which are optimal and near-optimal CE solutions with acceptable performance exist for the mMIMO systems but are faced with computation complexities and complications associated with matrix inversions in mMIMO systems. This has motivated several research works to explore the use of ML in CE for mMIMO systems [275]. The theoretical studies so far have shown promising results in the reduction of computational cost and achieving good performance when compared with the traditional approach.

The application of ML has also been considered in other use case scenarios such as UT localization, mMIMO aided IRS, spectral and energy efficiency, modulation, resource allocation, low-bit ADC systems, decoder, modulation detection, and beamforming. The majority of these works have considered the block-to-block approach while very few have considered an end-to-end approach. In addition, since the application of ML in communication systems is still an emerging area, most of the works reviewed are theoretical concepts and laboratory works. Although, efforts are being carried out to validate the use of ML in I-mMIMO systems [87]. Based on the existing literature, we find that some research works employ a data-driven approach while others are using the model-based approach to assist the performance of the data-driven approach. Thus, in our opinion, the model-based approach is likely to remain useful for the time being but the current research interest is indeed shifting towards the data-driven approach. As the journey to actual implementations and deployment of a data-driven approach may take a few years, several theoretical and practical questions need to be answered. These questions involve the complications associated with the design and training phases, the need for a framework that provides a generalized protocol that is service-oriented and user-centric, and practical online implementations of ML approaches.

VII. OPEN ISSUES

The open issues connected with the application of ML in mMIMO systems are discussed in this section in order to provide answers to RQ3. Some of the open issues identified in the literature include modular architecture, environment dependency, training, selection of AI techniques, and lack of a common framework.

A. MODULAR ARCHITECTURE

The PHY of the CM-MIMO system is built up with modular architecture in which each module is optimized based on different performance indices. Examples of such modules are ADC, decoder, baseband processor, modulator, and channel encoder which form part of the transmitter and are optimized block-by-block and not as the whole system. For the various aspects of I-mMIMO systems, the application of ML needs to be structured in order to provide a workflow that optimizes the end-to-end system [25], [33], [276]. Some works have shown the possibilities of application of the ML for end-to-end communication in I-mMIMO systems [114], [115].

B. ENVIRONMENT DEPENDENT

Most of the DL approaches have been designed to be adaptive to a particular environment. This leads to performance degradation in the mMIMO systems when there is a change in the statistical correlations. This introduces the challenge of retraining and relearning. Hence, the use of the transfer learning approach is seen as a viable option [223]. This raises the question of the possibility of the I-mMIMO BS to update its training model within the coherence time.

C. SECURITY

The shift from a model-based mMIMO communication paradigm to data-driven communication using AI opens up issues of security both at the PHY and network layer. Some of the security issues have been explored in [277], [278], [279], [280], and [281]. In [278], the effect of adversarial attack and jamming attack on CSI feedback in DL-based mMIMO were investigated, while in [279] and [280] spoofing attack and eavesdropper's attacks in [281] were investigated on the PHY. Although the use of the ML is advocated to mitigate security threats, however, a major issue pointed out in [35] is the delay in the detection of such threats.

D. TRAINING METHODS

One important aspect of ML is training which basically involves mapping input parameters to output functions based on the underlying structures of the mMIMO communication system. In wireless communication, this introduces the challenge of training time and computational complexity. Hence different approaches are being adopted. For instance, the use of ML techniques such as supervised and unsupervised methods requires a large amount of a priori labeled training and testing data. This can be difficult to implement in practical mMIMO systems. Another issue to consider is whether to implement online-training [107], [108], [109], [110] or offline training. The use of offline training models for real-time applications is prone to errors and inaccurate predictions. Hence, online training is advocated. For instance, transfer learning [223], [282], [283], [284], and adaptive learning methods are considered for online training in order to meet the time constraints and reduce training computational complexity and the ability to adapt to changes in the learning environment. The use of data from UTs for training purposes also raises the issue of privacy. To address this issue, the use of FL has been considered in [96], [101], [102], [103], [104], [105], and [285]. Although FL helps to solve privacy and bandwidth issues the challenge of reconstructing the local gradient vectors accurately at the central processing unit needs to be tackled [109]. Furthermore, UTs need to be equipped with the capability to handle ML algorithms efficiently with optimum power consumption. Another issue encountered in the use of ML is the methods and effect of handling missing data and sparse recovery [286] and the need to find the hyperparameter (number of layers, neurons) of the ANN. The use of deep unfolding is exploited to determine the hyperparameter of ANN for wireless communications via the use of iterative signal processing algorithms [287], [288].

VIII. FUTURE TRENDS

In this section, the RQ4 is addressed by pointing out the future direction we envisage in I-mMIMO systems.

A. I-mMIMO ENABLED APPLICATIONS

The I-mMIMO is currently being used to enable several technological applications in order to meet the unprecedented requirements of the B5G. Some of the technological applications are discussed as follows:

1) VISIBLE LIGHT COMMUNICATION

The use of mMIMO VLC system is considered a promising approach to improving communication capacity and spectrum efficiency [289], [290]. However, achieving an accurate CE in a large channel matrix where the communication link with LoS is dominant in VLC remains a challenge. Hence, the use of ML I-mMIMO systems is currently being explored to overcome this challenge [289], [290].

2) HIGH SPEED DEPLOYMENT

The application of mMIMO has been extended in high-speed mobile bandwidth deployments such as fast-moving autonomous vehicles [291], [292], [293], [294], vehicle-to-vehicle communication [295], and unmanned aerial vehicles (UAV) [187], [296], [297]. The use of I-mMIMO is expected to support the requirements of vehicle-to-everything (V2X) [298]. While the CM-MIMO systems seem promising in these areas, there are several issues that necessitate the application of I-mMIMO systems. For instance, the use of DL DoA was proposed to overcome the limitations of subspace and sparsity DoA estimation using mMIMO for autonomous vehicles [291]. On the other hand, the use of DRL in mMIMO systems was proposed to overcome the navigation challenges faced by UAVs by enhancing coverage and convergence [297]. Similarly, the ML techniques have been explored in [296] to increase energy efficiency in a hybrid precoding UAV-based mmWave mMIMO system. The use of ML aided mMIMO has been explored to predict link quality for vehicle-to-vehicle communication using the CSI between the BS and the vehicle-to-infrastructure in [295].

3) Space-AERIAL-TERRESTRIAL INTEGRATED NETWORKS (SATIN)

Space-aerial-terrestrial integrated networks (SATIN) are anticipated to play a major role in B5G networks [299]. In particular, space networks involve the use of satellite communication such as geostationary earth orbit (GEO), medium earth orbit (MEO), and low earth orbit (LEO) satellites [300]. Aerial networks consider both high-altitude platform stations (HAPS) such as balloons and kites, and low-altitude platform stations (LAPS) such as UAVs [301]. Meanwhile, terrestrial networks are expected to employ mmWave-aided mMIMO and Terahertz ultra-massive MIMO systems [302]. Unlike classical terrestrial networks, SATIN are able to provide ubiquitous coverage and ultra-high data rate. For example, [303] proposes to integrate LEO satellites with mMIMO to achieve the aforementioned goals. Nevertheless, the relative movement of the LEO satellites can cause time-varying network topology and intermittent links. These issues lead to key challenges in the CSI acquisition. To address this, one may explore I-mMIMO system [304].

As an alternative, HAPS has been proposed to provide wireless access in remote areas and for disaster recovery communications. Unlike space networks, HAPS can be used to provide enhanced capacity and coverage in urban and suburban areas as well as for data acquisition, computing, caching, and processing [305]. To facilitate these, HAPS with mMIMO has been considered [306]. Nevertheless, beamforming, interference, and model-based detection scheme require further studies [305], [307], [308]. In addition, LAPS can be used in a similar way as HAPS. But unlike HAPS, LAPS encounter limited size, weight, and power constraints [309]. Thus, optimal 3D beamforming, trajectory, and placement have to be considered. It is also worth noting that UAVs can be employed as aerial users [310]. Thus, in the context of mMIMO, it is necessary to address the pilot contamination, resource splitting, interference, and handover issues [311], [312].

4) PRECISION NETWORK PLANNING

Precision network planning involves network design and optimization that enables service providers to maximize return on investment. The emergency of B5G networks poses more challenges to network planning due to increasing data traffic, heterogeneous network, new use cases, and service demands coupled with environmental factors. To meet the stringent key performance indicator of B5G networks, ML is expected to play a vital role in timely network planning. This includes the ability to predict trends and detect anomalies, optimize power consumption based on usage patterns. In addition, research on the placement of ML functionalities in the network layer and resource allocation for the ML functionality is expected to dominate future research works. Research on radio resource management for different applications using ML techniques is expected to attract more research interest. An example is the use of DL-based feedback and precoding to maximize network throughput in the mmWave network in an mMIMO-enabled virtual reality (VR)/augmented reality (AR) system [313].

5) I-mMIMO IoT SYSTEMS

The adoption of mMIMO system for IoT communication has been presented in [314] due to the many advantages it offers for PHY communication. However, I-mMIMO system can be leveraged to increase the QoS, energy, and spectral efficiency by taking into account the behaviors and traffic patterns of IoT devices, age of information [315], delays, and latency requirements.

B. I-mMIMO SECURITY

As the concept of I-mMIMO matures, research on schemes to make I-mMIMO secure and robust towards different kinds of attacks will continue to attract research interest. Also, the use of ML techniques for the predictive detection of attacks on mMIMO systems is expected to draw several research interests. More studies on the vulnerabilities of ML techniques are expected in the deployment of I-mMIMO systems. As the future mMIMO systems are designed for IoT applications that have lightweight protocols and end-devices with low power consumption with low computing capabilities, new security policies and ML protocols are needed. A new security approach that takes into account accurate prediction, timely detection, and timely correction is needed for I-mMIMO systems.

C. GREEN I-mMIMO NETWORKS

An important area that needs to be explored in I-mMIMO is the application of ML to reduce the information communication technology (ICT) carbon footprint. The carbon footprint is described as the life cycle carbon equivalent emissions and effects that are related to a product or service [316]. The ICT carbon footprint can be categorized into embodied (extraction of raw materials, manufacturing, transport, and end of life) and operational impacts [317]. Due to the increasing effect of climate change and global warming [316], efforts need to be directed towards reducing the amount of carbon generated by the large deployment of mMIMO systems. This includes AI-driven techniques for reduction of power consumption [318] and tracking of carbon footprint for mMIMO deployments. Furthermore, the use of wireless power transfer/energy harvesting using I-mMIMO to enable zero energy devices (ZED) envisioned for 6G opens is expected to attract the attention of researchers [106]. More research works are needed for new I-mMIMO protocols that optimize the power consumption of the ZED.

D. DIGITAL-TWIN I-mMIMO

Digital-twin is an emerging area where information technology is integrated with operational technology. This enables the integration of physical objects and virtual objects [319]. The advancement of computational technology using quantum computing and ultra-high reliable network in 5G and B5G, is expected to pave way for digital-twin mMIMO systems. This will allow for real-time monitoring and processing of the physical I-mMIMO systems using virtual I-mMIMO systems.

E. TERAHERTZ I-mMIMO

The quest to meet the demand for Terabit-per-second (Tbps) using the terahertz-band band (0.3-10 THz) is attracting research interest. However, the constraints of high propagation loss in this band need to be overcome [320]. The use of I-mMIMO system is seen as a promising solution and hence more research works are expected in this area. Possible solutions include the use of ML in intelligent reconfigurable environment enabled I-mMIMO with 3D capabilities [320] and DRL-based multi-hop RIS-assisted hybrid beamforming scheme [321].

F. I-mMIMO FRAMEWORK

More research work is expected in defining a framework that accounts for ML network architecture or structures that are suitable for I-mMIMO systems. Also, frameworks required to aid the training process both at the PHY and medium access layers are needed. A framework that can account for the DL models, number of layers, optimization algorithm, and that are suitable for different I-mMIMO system analysis is needed. Standardization organizations have started consultation in order to define a framework for the application of ML in radio access networks. Examples are the 3GPP [122] and International Telecommunication Union (ITU) [123].

G. SELF ORGANIZED I-mMIMO

The use of ML in I-mMIMO systems is expected to play a major role in the deployment of B5G networks. These include self-optimization, self-configuration, and self-healing [34], [322]. For example, multi-agent RL is advocated in [27] in overcoming some of the issues of interference in the deployment of THz communications via self-organizing in B5G networks. More research works are expected in the application of ML for self-healing in the I-mMIMO systems [322], [323] and self-tuning beamforming [324] I-mMIMO systems.

H. I-mMIMO IRS DEPLOYMENT

More research work is expected in the use of ML to address some of the challenges faced in IRS-aided mMIMO systems. These include the CE complexity due to a large number of LIS elements [325], huge pilot overhead [127], [129], and deciding the optimal location of IRS and how the deployed IRS associate with different BSs or APs [325]. The use of ML in IRS aided mMIMO systems is expected to overcome the challenges faced in obtaining global CSI for distributed IRS networks [325] and reduction in complex operations for RIS configuration during channel coherence time [128].

I. NEW ML TECHNIQUES

For practical implementation of I-mMIMO systems, new ML techniques that are structured for wireless communication will continue to attract a great deal of interest. The use of adaptive learning techniques is expected to replace the traditional ML techniques where static data are divided into training and testing. Adaptive learning will enable the I-mMIMO systems to continuously adapt to change in the wireless environment with optimal performance. In addition, the cross-fertilization between data-driven and model-driven using mathematical model approaches for specific I-mMIMO tasks is expected to draw research interest. This will pave the way for hybrid I-mMIMO systems. More research works in exploring the application of FL for collaboration between I-mMIMO BS and UTs in heterogeneous networks and service demands are expected. Due to the challenges of hyper-parameter tuning in the application of ML in I-mMIMO more research works are required in the exploitation of deep unfolding.

J. I-mMIMO JCAS

The integration of RF and sensing capability enables the network to detect the presence of objects and some of the object's attributes using radars. This is known as joint communication and sensing (JCAS) [326], [327], [328]. The use of sensing capabilities in mobile networks provides opportunities for several use cases such as object detection and collision avoidance in vehicular networks. Research in vision-aided wireless communications is an emerging area [329], [330]. This combines wireless data and vision data in order to overcome blockage, assist in the prediction of mMIMO channel subspace, enhance hand-over mechanism, enable context-aware communication, and provide proactive network management [329], [330], [331]. Examples of application of ML techniques in vision-aided wireless communication have been explored in [329], [331], [332], and [330] with potential benefits. However, the deployment of JCAS opens up new challenges such as the need for signal processing for the detection of the presence and shape of objects, interference, optimal overheads, and enhanced protocols for different radar requirements [326]. In addition, the creation of an effective framework that captures scenario-dependent data and system configurations for vision-aided wireless communication is a promising area [329], [332].

K. NEXT GENERATION MULTIPLE ACCESS

Next generation multiple access schemes such as power-domain non-orthogonal multiple access (NOMA), code domain NOMA, and rate splitting multiple access (RSMA) are promising techniques that can be used in overloaded mMIMO systems with a much higher number of users if compared to available channel resource and spatial degrees of freedom [333]. NOMA not only enables multiple users to share the same orthogonal channel resource but also offers a spectral efficient way to multiplex users with different channel qualities and diverse quality of service requirements. Existing studies show that [334], [335], [336] the power domain NOMA is compatible with massive MIMO systems and delivers promising spectral efficiency improvement while minimizing the pilot contamination effect [337] if compared to conventional orthogonal multiple access (OMA). Future work of I-mMIMO with NOMA shall consider the use of ML to address the complex problem of joint optimization of NOMA power coefficients [338], [339], user clustering [336], beamforming [340], and other mMIMO parameters in taking into account network load, imperfect CSI, and imperfect hardware.

IX. CONCLUSION

An overview of ML in I-mMIMO systems has been presented in an attempt to answer the following research questions: RQ1: What are deployment methods for I-mMIMO systems? RQ2: What is the current research trend in the application of ML in I-mMIMO? RQ3: What are the challenges and open issues in the adoption of ML in I-mMIMO systems? RQ4: What are the future directions for ML in I-mMIMO systems? The deployment methods for I-mMIMO systems were presented. The application of ML in I-mMIMO research areas such as IRS aided systems, user localization, spectral and energy efficiency, modulation, low-bit ADC mMIMO systems, intelligent CF-mMIMO systems, mMIMO decoder, and CE and beamforming were presented. An overview of the I-mMIMO systems shows the plethora of works and the potential of ML in I-mMIMO systems. While I-mMIMO systems look promising, there are many theoretical and practical issues that need to be addressed. These open issues include the adoption of ML for PHY modular architecture, environment-dependent training, security challenges, training methods, selection of appropriate ML techniques, and lack of framework for easy adoption of ML-enabled mMIMO systems. Based on these challenges as well as the emerging technology, we outline the future research directions in I-mMIMO which include I-mMIMO enabled applications, security in I-mMIMO systems, green I-mMIMO networks, digital-twin I-mMIMO systems, terahertz I-mMIMO systems, self-organized I-mMIMO systems, I-mMIMO frameworks, I-mMIMO IRS Deployments, new ML techniques, I-mMIMO JCAS systems, and I-mMIMO aided next-generation multiple access schemes. It is expected that the research community will find this paper helpful by gaining an insight into the plethora of research works that are ongoing in the I-mMIMO systems.

ACRONYMS and TERMS

3D	Three dimensional.
3GPP	3rd generation partnership project.
4PAM	Quaternary pulse amplitude modulation.
5G	Fifth generation.
6G	Sixth generation.
8PSK	Eight phase shift keying.
16QAM-16	Quadrature amplitude modulation.
AP	Access points.
AS	Antenna selection.
AWGN	Additive white Gaussian noise.
ADC	Analog-to-digital converters.
AoD	Angle of departure.
ADCPM	Angle-delay channel power matrix.
AoA	Angle-of-arrival.
AI	Artificial intelligence.
ANN	Artificial neural network.
AMC	Automatic modulation classification.
AMR	Automatic modulation recognition.
BS	Base station.
B5G	Beyond fifth generation.
BFSK	Binary frequency shift keying.
CE	Channel estimation.
CF-mMIMO	cell-free mMIMO.
CPU	central processing unit.
CSI	channel state information.
CQF	combine-quantize-and-forward.
CPU	central processing unit.
CSI	channel state information.
CQF	combine-quantize-and-forward.
CV-DnCNN	Complex valued denoising CNN.
CM-MIMO	Conventional mMIMO systems.
CNN	Convolutional neural network.
DL	Deep learning.
MLP	Multilayer perceptron.
DNN	Deep neural network.
DTL	Deep transfer learning.
DAS	Distributed arrays of antennas.
ELM	Extreme learning machine.
FL	Federated learning.
FDD	Frequency division duplex.
FCNN	Fully connected neural networks.
GMSK	Gaussian minimum shift keying.
GP	Gaussian process.
I-mMIMO	Intelligent mMIMO.
ICT	Information communication technology.
IoT	Internet of things.
IRE	Intelligent radio environments.
IRS	Intelligent reflecting surface.
JCAS	Joint communication and sensing.
k-NN	k-nearest neighbor.
LIS	Large intelligent surface.
LSTM	Long short-term memory.
MIMO	Multiple input multiple output.
ML	Machine learning.
mMIMO	Massive MIMO.
mmWave	Millimeter wave.
MRC	Maximum ratio combining.
MMSE	Minimum mean square error.
MSK	Minimum shift keying.
NOMA	Non-orthogonal multiple access.

OFDM	Orthogonal frequency division multiplexing.
OMA	Orthogonal multiple access.
PO	Phase-offset.
PHY	Physical layer.
DQPSK	Differential quadrature phase shift keying.
QPSK	Quadrature phase shift keying.
QoS	Quality of service.
QF	Quantize-and-forward.
RAU	Remote antenna units.
RB	Resource block.
RL	Reinforcement learning.
RIS	Reflecting intelligent surface.
RMS	Reconfigurable meta-surfaces.
RNN	Recurrent neural networks.
RSS	Received signal strength.
RSMA	Rate splitting multiple access.
SDR	Software defined radio.
SLR	Systematic literature review.
SINR	Signal-to-interference-and-noise-ratio.
SNR	Signal-to-noise ratio.
TDD	Time-division duplex.
ToA	Time-of-arrival.
PRISMA	Preferred reporting items for systematic reviews and meta-analyses.
UT	User terminals.
V2X	Vehicle-to-everything.
WoS	Web of Science.
ZF	Zero forcing.
ZED	Zero energy devices.

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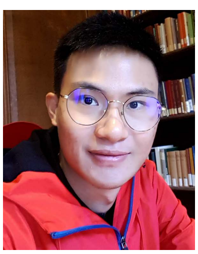

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