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SURVEY

Enhancing QoS and RF-EMF Radiation Using RSMA and AI in 6G Networks: A Comprehensive Survey

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ABSTRACT The sixth generation (6G) wireless networks are envisioned to deliver unprecedented levels of connectivity, ultra-reliable low-latency communication (URLLC), and energy efficiency while addressing public concerns about radiofrequency electromagnetic field (RF-EMF) exposure. Rate-Splitting Multiple Access (RSMA) has emerged as a promising multiaccess technique that flexibly manages interference and supports a broad range of Quality of Service (QoS) requirements. In parallel, the integration of artificial intelligence (AI), including machine learning (ML) and reinforcement learning (RL), has become essential for dynamic resource optimisation, proactive decision making, and real-time adaptation in complex and dense wireless environments. This survey presents a comprehensive overview of RSMA's operational principles, with a focus on its encoding/decoding architecture using low-density parity-check (LDPC) and polar coding and how it enhances spectral and energy efficiency compared to traditional multiple access schemes. It also presents the mathematical framework for both the RSMA scheme and the RF-EMF evaluation. The survey also explores AI-driven strategies for optimising RSMA, including power control, beamforming, and user scheduling, while minimising RF-EMF exposure. We examine the regulatory thresholds provided by IEEE, FCC, and ICNIRP, focusing on exposure-aware RSMA models that balance RF safety with performance demands in relation to system constraints. Furthermore, we discuss system-level trade-offs between QoS and RF-EMF exposure and system performance metrics such as bit error rate (BER), latency, spectral efficiency, and specific absorption rate (SAR) levels. This survey identifies open challenges, including real-time AI deployment, scalability, and security, and discusses future research directions, such as hybrid multiple access models, privacy-preserving ML, and AI-RSMA-6G integration. Finally, this survey serves both as a reference guide and a basis for future research on the safe, intelligent, and high-performing deployment of RSMA in 6G networks, which optimises both user experience and environment.

INDEX TERMS 6G networks, artificial intelligence, deep reinforcement learning, machine learning, RF-EMF, RSMA, QoS.

LIST OF ABBREVIATIONS

In this section, we define the abbreviations that are the most frequently used.

5G	Fifth Generation.
6G	Sixth Generation.
AI	Artificial Intelligence.
AP	Access Point.
BER	Bit Error Rate.
BPSK	Binary Phase-Shift Keying.
CSI	Channel State Information.
DBS	Distributed Basestation.
DL	Downlink.
DRL	Deep Reinforcement Learning.

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EE	Energy Efficiency.
EI	Exposure Index.
EMF	Electromagnetic Field.
FCC	Federal Communication Commission.
FL	Federated Learning.
GNN	Graph Neural Network.
ICNIRP	International Commission of Non-Ionising Radiation Protection.
IEEE	Institute of Electrical Electronics Engineers.
LDPC	Low-Density Parity-Check.
MA	Multiple Access.
MIMO	Multiple-Input Multiple-Output.
ML	Machine Learning.
NGN	Next Generation Network.
NOMA	Non-Orthogonal Multiple Access.
OMA	Orthogonal Multiple Access.
PD	Power Density.
QoS	Quality of Service.
QPSK	Quadrature Phase-Shift Keying.
RF	Radio frequency.
RF-EMF	Radio Frequency Electromagnetic Field.
RL	Reinforcemnt Learning.
RSMA	Rate-Splitting Multiple Access.
SAR	Specific Absorption Rate.
SDMA	Space Division Multiple Access.
SE	Spectral Efficiency.
SIC	Succesive Interference Cancellation.
SINR	Signal-to-Interference-Noise Ratio.
SL	Supervised Learning.
UE	User Equipment.
UL	Uplink.
UnL	Unsupervised Learning.

I. INTRODUCTION

The sixth generation (6G) of wireless communication is poised to transform the landscape of connectivity by enabling ultrafast, highly reliable and intelligent communication systems. As a natural evolution beyond the fifth generation (5G), 6G is expected to support extreme data rates in the order of terabits per second, ultra-low latency in submilliseconds, and massive connectivity for intelligent devices [1]. It will also introduce ubiquitous integration of artificial intelligence (AI), edge computing, and intelligent surfaces to meet the growing demand for seamless connectivity across diverse applications such as holographic communications, extended reality (XR), digital twins, autonomous systems, and smart healthcare.

The evolution of wireless communication from the first generation (1G) to 6G reflects a continuous effort to improve user experience and system performance along with their unique multiple access techniques [2]. Wireless communication was launched in the 1980s with the 1G analogue networks using frequency-division multiple access (FDMA), with few usages of communication devices and services. Wireless communication grew into a commercial success with the introduction of a global system for mobile communication (GSM) in the 1990s, making the second generation (2G) of wireless networks using time division multiple access (TDMA) [1]. 2G brought digitalisation into mobile communication, as minimal data services were introduced. Code-division multiple access (CDMA) revolutionised mobile communication with high-data services in the early 2000s with the introduction of the third generation (3G) network.

In 2009, the fourth generation (4G) network known as long-term evolution (LTE) was commercially launched with orthogonal frequency division multiple access (OFDMA) and multiple-input multiple-output (MIMO) technologies. This exponentially increased the use and services of mobile communication. 5G was launched commercially in 2000 and has turned around very high quality of service (QoS) use cases from humans to machines to things and to the verticals with its enabling technology of massive MIMO, OFDMA, and/or non-orthogonal multiple access (NOMA). The sixth generation (6G) network is expected to be launched by 2030 [3] and envisions how humans will interact with virtual services in years to come [4]. Rate-Splitting Multiple Access (RSMA) has emerged as its promising multiple access (MA) technique because it flexibly splits and manages interference by decoding part of it and treating the rest as noise.

The MA techniques are fundamental to any cellular network, as they determine how users share finite spectrum resources. In traditional systems, orthogonal multiple access (OMA) techniques such as TDMA, FDMA, and OFDMA have been widely used to allocate orthogonal resources to users, ensuring minimal interference. To meet the growing demands for spectral efficiency (SE) and user fairness, NOMA was introduced in 5G. NOMA allows users to share the same time-frequency resources through multiplexing of the power or code-domain. However, it suffers from scalability issues and decoding complexity, particularly in dense and heterogeneous environments.

For 6G, there is a need for a more robust and flexible access framework that can dynamically adapt to varying channel and network conditions, user demands, and QoS requirements. This brings attention to RSMA, a promising candidate that generalises and outperforms existing MA schemes by better managing interference and supporting user heterogeneity [5]. RSMA uses an encoded rate-splitting method at the transmitter to split users' messages into various common and private messages and superimpose them before transmitting them concurrently to the receiver [6]. At the receiver, successive interference cancellation (SIC) is done on the encoded message to flexibly decode the common and private messages in that order, allowing partial interference decoding, while the private part is decoded individually. With SIC, RSMA reduces interference by default [7]; thus, it is a reliable interference management scheme for massive MIMO networks.

RSMA has the advantage of partially decoding interference from multiple user equipment (UE) (as in NOMA), as well

as treating it as noise (as in OMA) [8]. RSMA is a good and promising scheme for multi-antenna network uplink (UL) and downlink (DL) [9]. As the number of UE increases in the network, the number of common signals increases exponentially. This access method requires each UE to decode and cancel a fixed set of common messages and then the UE's private message; this would increase the complexity of the network. Therefore, the efficacy of the RSMA scheme is important.

Considering the rapid evolution of UE and multimedia services, the envisioned 6G networks must cope by consequently providing unprecedented ultra-massive connectivity, ultra-high data rates, fairness, extremely low latency, EE, SE, and environmental sustainability [10]. The 6G network must address not only performance but also critical concerns such as interferences, radiofrequency electromagnetic field (RF-EMF) exposure, and energy consumption. The exponential growth in connected devices escalates to increase in the RF-EMF exposure, which demands a careful balance between performance and safety. Traditional MA techniques such as OMA and NOMA face challenges under such ultradense connectivity and heterogeneous service requirements.

RSMA is considered to be a more fit access method compared to traditional MAs [5], [6], [11]. However, despite the inherent advantages of RSMA, achieving its full potential within 6G networks requires intelligent, adaptive resource management that traditional methods cannot provide. The envisioned 6G networks will be heavily softwarised and orchestrated by artificial intelligence (AI), particularly machine learning (ML) techniques embedded within programmable network architectures [12]. Still, integrating RSMA with ML-based dynamic optimisation to simultaneously balance QoS demands, interference management, RF-EMF minimisation, and EE remains an open and critical research challenge.

Moreover, the need to reduce the exposure from RF-EMF radiation introduces additional complexity in the design of resource allocation strategies. Achieving near-zero power transmission while maintaining high QoS metrics, such as SE and EE, without breaching RF-EMF exposure limits, calls for the development of innovative ML-driven schemes that are both low in computational complexity and highly effective in real-time decision-making. There is a clear gap in the existing literature on how RSMA, when combined with machine learning approaches like deep reinforcement learning (DRL), can dynamically and intelligently optimise resource allocation, manage interference, and control RF-EMF exposure in a scalable manner suited for 6G and beyond networks.

Thus, this paper addresses the need for an integrated framework that leverages RSMA principles and machine learning algorithms to develop adaptive, efficient, and green communication strategies. It aims to bridge the gap between theoretical potential and practical deployment by designing and validating a robust RSMA-ML-based system capable of ensuring sustainable, high-performance wireless communication under the challenging conditions expected in future 6G environments.

The key contributions of this manuscript are as follows.

- *This paper provides a comprehensive review of the theoretical foundations and applications of RSMA in 6G networks.*
- *The integration of AI/ML with RSMA is explored, and AI/ML-driven approaches are presented to optimize RSMA resource management in 6G systems. Furthermore, techniques to mitigate RF-EMF exposure while preserving QoS are discussed.*
- *A comparative analysis of OMA and NOMA is conducted, identifying key performance metrics for evaluating multiple access techniques.*
- *The main novelty of this survey is the comprehensive explanation and review of the integration of RSMA concept, AI optimisation methods, in a 6G network, with consideration of QoS and RF-EMF. Importantly, no existing survey reviewed RF-EMF exposure mitigation in a RSMA-6G network using AI-based methods.*
- *Finally, a roadmap for future research and development is outlined, highlighting critical directions that require further investigation.*

The rest of this paper is organised as follows. Section II compares related surveys in the literature. Section III explains the fundamentals of RSMA in 6G networks. Section IV delves into AI techniques for RSMA. Section V discusses the RF-EMF exposure and QoS trade-offs in RSMA. Section VI explores the performance evaluation used for the RSMA technique in 6G networks. Section VII presents open challenges and future research directions. Lastly, some conclusions are drawn in Section VIII.

II. RELATED SURVEY ARTICLES

This section compares and distinguishes this survey with existing related surveys and introduces readers to other major areas that are focused on in this survey in the literature. This survey comprehensively discusses RSMA, 6G, AI, and RF-EMF. Thus, existing related surveys are focused on these areas.

Several surveys have reviewed RSMA. The survey in [13] presented a comprehensive review of the key MA technologies in aerial networks, with much focus on RSMA. The authors also discussed related open and future research directions. Similarly, another comprehensive survey in [14] focused on the fundamentals of RSMA by comparing it with existing MA methods, challenges, and its future research trends. In addition, in [15], the authors gave an overview of RSMA advancements in green communications. The survey introduced and developed some RSMA beamforming algorithms that optimised energy efficiency (EE), and compared the EE of the RSMA method with other MA with the conclusion that the superior results of RSMA make it a good candidate for green communication networks.

There are a couple of surveys on AI, which is another focus area in this survey. In [16], the authors presented

TABLE 1. A summary of existing related surveys and their focus areas.

Survey Ref.	AI	RSMA	6G	RF-EMF	Focus areas
W. Jaafar et al. [13]	×	✓	✓	×	Review of the key MA technologies in aerial networks, with much focus on RSMA
Y. Mao et al. [14]	×	✓	×	×	Comparison with existing MA schemes in terms of their overall frameworks, performance, and complexities
X. Zhou et al. [15]	×	✓	×	×	Developed some RSMA beamforming algorithms and compared the EE of the RSMA method with other MA
D. C. Nguyen et al. [16]	✓	×	×	×	Overview of data-driven AI-related studies in wireless networks, wireless data-driven AI architecture, AI solutions, its applications in network optimization, and research challenges
H. Mahmoud et al. [17]	✓	×	×	×	Review of prior studies on generative AI (GAI), its use cases, opportunities, challenges, applications, solutions and research gaps
Y. Siriwardhana et al. [4]	✓	×	×	×	Integration of AI and 6G networks and focused primarily on ensuring the security and privacy of the network using AI, the challenges, and solutions
Y. Usman et al. [18]	✓	×	×	×	The roadmap for the alliance of AI, ML, LLM, and 6G networks
M. Chowdhury et al. [19]	×	×	✓	×	6G communication systems, such as requirements, technologies, applications, challenges, and open research gaps
V. T. K. Anh [20]	✓	×	✓	×	Opportunities, challenges and applications of AI in 6G networks
B. Clerckx et al. [21]	✓	×	✓	×	Overview of MA techniques, the roadmap to an intelligent and multifunctional 6G network, and future research areas
S. Faye et al. [7]	×	×	×	✓	Overview on RF-EMF-aware network planning strategies and summarised the open research gaps
A. Ajibare et al. (This present survey)	✓	✓	✓	✓	Comprehensive overview and integration of RSMA, 6G, AI, and RF-EMFs

recent data-driven AI related studies in wireless networks, proposed a wireless data-driven AI architecture, gave an overview of AI solutions and thier applications in network optimization, and finally discussed the research challenges. The survey [17] reviewed previous studies on generative AI (GAI) by highlighting use cases, opportunities, and challenges; examined its applications and solutions; and identified its research gaps. In addition, the authors in [4] focused on intelligent network orchestration and management of the 6G networks. The survey comprehensively discussed the integration of AI and 6G networks and focused primarily on ensuring the security and privacy of the network using AI, the likely challenges, and solutions. Similarly, the authors in [18] presented a roadmap for the alliance of AI, ML, large language models (LLM), and 6G networks.

Another focus of this survey is on 6G networks. The authors in [19] addressed some major areas in 6G communication systems, such as requirements, technologies, applications, challenges, and open research gaps. The survey in [20] discussed the opportunities, challenges, and applications of AI in 6G networks. In [21], the authors focused on the overview of multiple access techniques and the roadmap to an intelligent and multifunctional 6G network.

The last area of focus of this survey is RF-EMF; not many surveys have been written on this area. The authors in [7] provided an overview on RF-EMF-aware network planning strategies and summarised the open research gaps related to this solution. Our survey is the first survey to provide a comprehensive review and overview of techniques, challenges, open research gaps, and proposed AI solutions to 6G RF-EMF exposure challenges.

The comparisons are summarised in Table 1.

III. FUNDAMENTALS OF RSMA IN 6G NETWORKS

RSMA is based on the concepts of rate-splitting, partial decoding, superimposition and superposition coding, and SIC as illustrated in Fig. 1.

A. RATE-SPLITTING APPROACH AND SUPERPOSITION CODING

At the core of RSMA is the rate-splitting approach, where each user K with message M is divided into a common part c (to be decoded by all users) and a private part p (for its specific user). This enables partial decoding of interference (through the common part) and partial treatment of interference as noise (in the private part). Thus, achieving balanced interference management

$$M_{k,i}, \quad \forall i\{c, p\}. \tag{1}$$

At the transmitter, the split messages are superimposed using superposition coding, a technique in which the common message is encoded into a signal meant for all users and each private message is encoded individually, and the signals are linearly combined into one signal for transmission over the shared channel. RSMA generalises and unifies traditional OMA and NOMA. It behaves similar to space division multiple access (SDMA) if only private messages are transmitted, and it resembles multicast if only a common

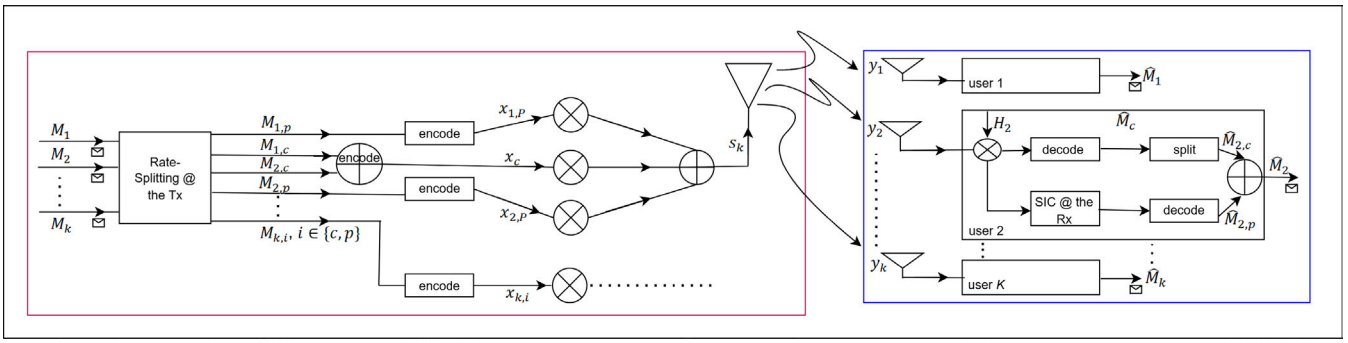


FIGURE 1. Signal model illustrating the RSMA-based user message transmission framework.

message is transmitted [8]. With both, RSMA dynamically adapts to user channel conditions and interference levels.

B. SUCCESSIVE INTERFERENCE CANCELLATION IN RSMA

At the receiver side, SIC plays an essential role. Each user first decodes the common message, treating all private messages as noise. Once decoded, the user removes the common signal from the received signal through SIC. Thereafter, the user decodes its own private message with reduced interference. This successive decoding enables each user to separate and recover its own data while reducing the impact of interference. The main benefit of adopting SIC in RSMA is that it enhances decoding performance by removing interference layers. It also reduces error propagation compared to fully non-orthogonal methods [5]. RSMA enhances robustness against interference and provides stable performance under various user channel conditions, especially when considering heterogeneous SNRs [22], [23].

C. MATHEMATICAL MODEL OF RSMA

The RSMA system model in Fig. 2 can be represented for single-cell and multi-cell networks as shown in Fig. 3. The total transmit signal for user k with subcarrier j is:

$$s_k^j = P_{k,c}^j \, x_{k,c}^j + \sum_{\kappa=1}^{K} P_{k,p}^j \, x_{k,p}^j \quad \forall j \in J, \tag{2}$$

where $P_{k,c}^j$ is the power allocated to the common encoded message $x_{k,c}^j$, and $P_{k,p}^j$ is the power allocated to the private encoded message $x_{k,p}^j$ for user k; subject to power constraint:

$$P_{k,c}^j + \sum_{j=1}^{J} P_{k,p}^j = P_k^j. \tag{3}$$

D. RSMA ENCODING PROCESS

To ensure reliable and efficient transmission over multiple noisy wireless channels, robust channel coding techniques such as polar codes and low-density parity-check (LDPC) codes are integrated into the RSMA system. These codes are applied to both common and private signals before transmission, providing resilience against noise and fading.

The RSMA encoding process comprises several stages, including message splitting, channel encoding, modulation, and superposition coding. Specifically, common and private messages are encoded separately, potentially utilizing different coding techniques tailored to the system's hardware complexity and performance requirements. The message splitting process involves dividing the user's message $M_{k,i}$ into a common message $M_{k,c}$ and a private message $M_{k,p}$, which are then encoded into $x_{k,c}$ and $x_{k,p}$, respectively, using distinct encoders.

1) POLAR ENCODING FOR COMMON MESSAGES

Polar codes are capacity-achieving for symmetric binary-input discrete memoryless channels [24]. The codes are preferred for common messages due to their low complexity and support for SIC decoding at the RSMA receiver. The polar encoding process involves transforming the common bit sequence using the Kronecker products of the generator matrix G_k, where bits are frozen based on reliability, resulting in a block of encoded bits ready for modulation.

2) LDPC ENCODING FOR PRIVATE MESSAGES

In contrast, LDPC codes, characterized by sparse parity-check matrices, are employed for private messages due to their strong error correction capabilities at high spectral efficiencies. The LDPC encoding process involves encoding the private bitstream using a parity-check matrix H, resulting in a codeword vector x that satisfies the condition $H * x^T = 0$. The encoded bits are then passed to the modulator for transmission.

E. MODULATION

Before encoded messages are superimposed for transmission, both encoded streams (common and private) are modulated using BPSK [25], QPSK [26], [27], or QAM [28] and are ready for superposition.

F. SUPERPOSITION CODING

Power is strategically allocated between common and private signals. Superposition coding combines the modulated common and private symbols linearly as s_k, usually in a stage

called a linear precoder [26], where the RSMA precoding algorithm resides [29]. This composite signal is transmitted over the wireless channel [28].

G. RSMA DECODING PROCESS

At the receiver, each user employs the SIC technique to decode the transmitted signals. The decoding process involves a layered code structure, where the common message is decoded first, followed by its subtraction from the received signal, thereby enabling a clearer and more efficient decoding of the private message.

The received signal at UE_k which is affected by channel gain, interference, and noise, is given by [30]

$$y_k^j = H_k^j \left(P_{k,c}^j \, x_{k,c}^j + \sum_{\kappa=1}^{K} P_{k,p}^j \, x_{k,p}^j \right) + N_+ \quad \forall j \in J. \tag{4}$$

1) COMMON MESSAGE DECODING

In the first step of the SIC process, all users UE_k decode the common stream. The signal-to-noise plus interference ratio (SINR) is a critical metric in determining the decoding performance of the common message, expressed as [9]

$$\Upsilon_{k,c}^j = \frac{P_{k,c}^j \left| H_k^j \, x_{k,c}^j \right|^2}{\sum_{\kappa=1}^{K} P_{k,p}^j \left| H_k^j \, x_{k,p}^j \right|^2 + N_0} \quad \forall j \in J, \ \forall K \in \kappa. \tag{5}$$

In polar encoding, the user applies successive cancellation (SC) or successive cancellation list (SCL) decoding, where bit-channel reliability is used to efficiently retrieve the original message and perform interference cancellation once decoded. These depend on frozen bit positions and a known code structure. Based on the channel model's log-likelihood ratios (LLRs), the decoder produces estimated bits. Alternatively, the LDPC decoding technique is another reliable error correction used in RSMA, which is based on iterative belief propagation (BP) algorithms.

After the common message $x_{k,c}$ is successfully decoded as $\widehat{M}_{k,c}$, it is subtracted from the received signal y_k^j to obtain a resulting signal $\acute{y}_k^j$. i.e.

$$\acute{y}_k^j = y_k^j - \widehat{M}_{k,c} \quad \forall K \in \kappa. \tag{6}$$

The SINR of the decoded private message can be expressed as [9]

$$\Upsilon_{k,p}^j = \frac{P_{k,p}^j \left| H_k^j \, x_{k,p}^j \right|^2}{\sum_{k' \neq \kappa}^{K} P_{k',p}^j \left| H_k^j \, x_{k',p}^j \right|^2 + N_0} \quad \forall j \in J, \ \forall K' \neq \kappa. \tag{7}$$

2) PRIVATE MESSAGE DECODING

The remaining signal mostly contains the private stream for that user. With LDPC codes, the user performs BP decoding based on the Tanner graph of the LDPC code, which iteratively updates the bit probabilities based on the check and variable node structure until convergence or maximum iteration is reached [30].

Similarly, the private message $x_{k,p}$ is correctly decoded as $\widehat{M}_{k,p}$, subtracted from the received signal $\acute{y}_k^j$ and then reconstructed as

$$\acute{y}_k^j - \widehat{M}_{k,p} \quad \text{or} \quad y_k^j - \widehat{M}_{k,c} - \widehat{M}_{k,p}. \tag{8}$$

The successive decoding and signal-to-noise ratio (SNR), without interference, becomes [8]

$$\Upsilon_{k',p}^j = \frac{P_{k',p}^j \left| H_k^j \, x_{k',p}^j \right|^2}{N_0}. \tag{9}$$

Conclusively, the total decoded message $\widehat{M}_k$ for UE_k is the combination of $\widehat{M}_{k,c}$ and $\widehat{M}_{k,p}$. The total SINR of message $\widehat{M}_k$ is

$$\Upsilon_{k,i}^j = \Upsilon_{k,c}^j + \sum_{k' \neq \kappa}^{K} \Upsilon_{k,p}^j, \tag{10}$$

where N_0 is the power spectral of the Gaussian noise. The achievable rate of the decoded message $\widehat{M}_k$ is [9]

$$R_{k,i} = B_j \log_2 (1 + \Upsilon_{k,i}^j). \tag{11}$$

For both encoding and decoding processes, RSMA may use the same encoder type for both layers to simplify hardware. However, polar codes are preferred for their structured nature and compatibility with SIC in RSMA, especially in the common layer. Whereas LDPC codes are ideal for high-throughput, low-latency applications in the private layer.

H. COMPARISON OF RSMA VERSUS OMA VERSUS NOMA

While RSMA is recognized for its effective interference management capabilities compared to other multiple-access techniques, its performance can be impacted by increasing user density. As the number of users increases, so does the interference level and complexity of SIC, which can lead to partial interference during common message decoding. Furthermore, perfect SIC is crucial for reliable private message decoding. Therefore, further investigation and optimization of RSMA are warranted to fully realize its potential.

Recent studies have identified RSMA as a promising candidate for next-generation networks (NGNs). This is well substantiated in a thorough review of RSMA done in [22]. A comprehensive tutorial was presented in [31]. The authors showed how RSMA outperforms other multiple access methods such as OMA, SDMA, and NOMA. The authors provided answers to many frequently asked questions (FAQs) about RSMA.

In [30], a Q-RSMA scheme was proposed; the scheme decodes the common message without interference. Thus, reducing the complexity of the SIC in the detection of private messages, and maximises the sum rate of the users in the network. The authors confirmed that the scheme outperforms

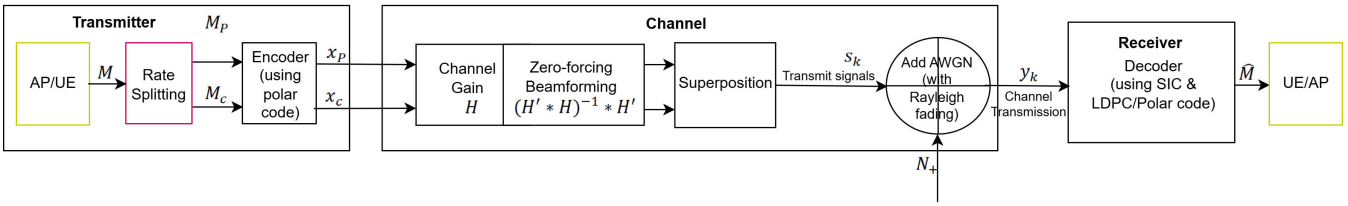


FIGURE 2. RSMA system model.

TABLE 2. Comparison of RSMA, OMA and NOMA.

Technique	Spectral efficiency	Complexity	Fairness
OMA [31]	Low	Low	Medium
NOMA [31], [30]	High	High	Low
RSMA [31], [30]	High	Moderate	High

NOMA and other RSMA schemes in terms of network efficiency, latency, and interference management.

A RSMA resource allocation algorithm was presented in [9], to solve a non-convex problem that maximises the sum rates in the network. The author concluded that the three-stage scheme provides a better rate outcome and less computational complexity compared to the OMA algorithms.

The authors in [32], proposed a RSMA technique for the C-RAN DL network. The approach leverages a linearly increasing common message strategy, where the common message power grows with the number of UE in the network. By employing hierarchical clustering for decoding common messages, the proposed RSMA scheme demonstrated superior performance compared to conventional multiple access methods, including traditional RSMA, as validated through numerical analysis.

In [33], Yang et al. proposed a RSMA algorithm that maximised the sum-rate subject to the transmit power and the decoding order of the APs. The results showed substantial performance in the sum-rate achieved compared to other multiple access methods. In [8], the author demonstrated the performance of RSMA for a UL wireless network. The results showed how finite blocklength can affect throughputs and error probabilities. Table 2 compares RSMA with other multiple access techniques.

IV. AI TECHNIQUES FOR RSMA OPTIMISATION

RSMA has emerged as a highly suitable multiple access technique that could support the requirements of the excepted 6G networks of extreme connectivity, ultralow latency, and especially intelligent decision-making. However, realising the full potential of the integration of both 6G networks and RSMA requires the addition of advanced optimisation techniques, and not just the traditional, heuristic or convex optimisation algorithms [34], [35], [36]. Further integration of AI, including ML and deep learning, plays a pivotal role in optimising the 6G-RSMA parameters such as the rate-splitting ratio, power allocation, data rate, beamforming vectors, interference, and RF-EMF radiation exposure.

A. WHY AI/ML FOR RSMA?

The integration of AI/ML with RSMA is motivated by the complexity of optimising multiple interdependent variables, including common and private message rate allocations, user clustering, power budget, and allocation across message layers, and beamforming under imperfect channel state information (CSI), scheduling, and user prioritisation [37]. Conventional optimisation methods are often limited by their inability to adapt in real-time to dynamic wireless environments and may struggle with high-dimensional and non-convex problems. In contrast, AI/ML enables the development of intelligent, self-learning models that can efficiently handle complex resource management tasks. By learning optimal strategies from data, AI/ML can adapt to changing environments in real-time across various channel conditions and uncertainty.

1) TRADITIONAL OPTIMISATION TECHNIQUES VERSUS AI/ML-DRIVEN SOLUTIONS

AI-powered optimisations in 6G-RSMA ultimately reduce network latency, one of the main motivations of 6G networks [38]. It leverages AI's automation, scalability, and learning capabilities in real-time wireless environments. Unlike traditional optimisation methods that use exhaustive search and sometimes convex programming, AI-based optimisations are computationally inexpensive and suitable for real-time adaptation in 6G [2].

Trained AI models, such as DRL, can eliminate the need for real-time mathematical optimization, enabling agents to instantly infer optimal power allocation and beamforming parameters from input features such as CSI. This approach significantly reduces processing delay. Additionally, AI can be leveraged for efficient load management by dynamically redistributing virtual network topology in edge cloud computing, as demonstrated in [39].

AI models, especially deep learning and federated learning architectures, are designed to scale. These models handle ultra-dense systems with massive-MIMO without linearly increasing computational complexity. Compared to traditional optimisation techniques, federated learning models distribute computation to edge devices [40]. Thus, preserve privacy, prevent bottlenecks in decision making, and reduce computational delays in dense networks due to their scalability.

AI-based optimisation models learn the dynamics of the network, such as user mobility, traffic patterns, interference,

and RF-EMF radiation trends, and proactively fine-tune network resources. A DRL agent can predict when a user is about to enter a high interference zone and preventively adjust his allocated power and other network resources [41]. This proactive learning and forecasting capability will adjust the common and private split in RSMA, which transforms to sustained high data rates under such demanding conditions, unlike traditional optimisation techniques.

2) CHALLENGES IN DYNAMIC POWER ALLOCATION, BEAMFORMING, USER SCHEDULING

While AI-based techniques offer promising solutions for optimising RSMA in 6G systems, they also introduce challenges in dynamic power allocation, beamforming, and user scheduling. Specifically, models such as DNN and DRL may suffer from non-convex objective functions due to complex constraints [42].

Moreover, misaligned reward functions in reinforcement learning (RL) can lead to suboptimal or unstable power allocation policies. Additionally, AI models may struggle to generalise across different environments, such as varying network densities or mobility scenarios [43], potentially resulting in QoS constraint violations and instability.

Furthermore, AI-based optimisation models require large, diverse, and labelled datasets for training, validation, and testing, as well as specialized hardware with sufficient power, memory, and computational resources to meet strict inference deadlines and remain latency-tolerant [44]. Addressing these challenges is crucial to ensure safe, scalable, and real-time operation of AI-based optimisation models in future 6G networks.

B. AI/ML TECHNIQUES FOR RSMA

There are different AI models that can be used to optimise network resources in the 6G-RSMA networks. These models can be ML-based, DL-based, or a hybrid of both and can be further categorised based on their learning taxonomy.

1) SUPERVISED LEARNING

Supervised learning (SL) algorithms are trained from generated datasets and mainly compute their optimal solutions offline. SL models used in RSMA optimisation include convolutional neural networks (CNNs) [45] and deep neural networks (DNNs) [46]. These algorithms are used to predicte user clusters for optimal scheduling and to predict optimal power allocations or rate-splitting ratios for a given CSI. The SINR values of the labelled datasets can be used to predict the split of power between common and private streams. Zhang et al. [47] implemented CNNs to estimate RSMA precoders from historical CSI, resulting in a significant reduction in computational time while maintaining optimal performance. In [48], the authors solved a resource allocation problem with a regression-based SL algorithm that obtained the solution in a shorter implementation time compared to an optimisation solver.

2) UNSUPERVISED LEARNING

Unlike SL, datasets for unsupervised learning (UnL) models are unlabelled. UnL determines hidden patterns in unlabeled data. UnL models can be used in RSMA where there are no labelled training data and for clustering in interference management. UnL models use clustering algorithms such as K-means, density-based spatial clustering of applications with noise (DBSCAN) [49], and dimensionality reduction methods such as principal component analysis (PCA) and autoencoders help identify user groups or spatial interference structures, thus reducing inter-user interference. UnL, such as graph neural networks (GNNs), can be integrated with self-organising maps [50] to model topology-aware scheduling. A predictive approach using an unsupervised classifier to retrain AI/ML models was presented in [51]. This predite when to retrain models to avoid degradation and inefficient network utilisation.

3) REINFORCEMENT LEARNING

RL models are used to dynamically optimise in time-varying networks. RL models are used for adaptive power control where the algorithm learns optimal power allocation policies over time. RL models used in RSMA optimisation include policy gradient, Monte Carlo, Q-learning, and deep Q network (DQN) methods [52]. These methods are mostly considered for sequential decision-making tasks and when the rewards are throughput, fairness index, and EE. In RL schemes, agents learn to adapt the RSMA parameters under dynamic channel conditions and decide on the best user scheduling and beamforming vector at each time slot based on the maximum reward. An outcome that is usually more robust and rewarding than most traditional methods.

4) DEEP REINFORCEMENT LEARNING

DRL models combine the power of deep learning with RL for high-dimensional problems. DRL algorithms enable joint optimisation of RSMA message splitting, resource allocation, beamforming, and adaptive power allocation [53]. In the DRL framework, each private message represents a DRL agent [54]. Popular DRL models include deep deterministic policy gradient (DDPG), proximal policy optimisation (PPO), and Actor-Critic methods. The authors in [53] and [55] show how the DRL model maximise SE in massive MIMO and dense networks by making DRL agents learn the policies. Furthermore, DRL can be used to model a realistic SIC receiver that uses RSMA communication from the transmitter [56].

5) FEDERATED LEARNING

FL trains models collaboratively without centralised data and preserves user privacy. FL models are preferred for decentralised privacy-preserving RSMA optimisation across distributed user devices, as they enable training from edge devices and are good for model generalisation. Different studies have explored FL for distributed RSMA optimisation,

TABLE 3. Applications of AI models in RSMA-based 6G networks.

Optimisation Task	AI Model	Ref.	Benefit
Power allocation	SL, DRL	[48], [56], [55], [53]	Adaptability to channel variations
Rate-splitting ratio	DRL, DNN, Actor-Critic	[56], [46], [53]	Enhanced throughput under interference
Beamforming	DQN, CNN, DDPG	[53], [60], [45], [47]	Improved spatial multiplexing
User scheduling	Q-Learning, DQN	[54]	Fairness and QoS balancing
Resource allocation under imperfect CSI	PPO, Meta-RL	[53], [48]	Robustness against channel uncertainty

and transfer learning to adapt models across different network settings without retraining from scratch. In [57], the authors compared the FL and baseline centralised schemes and concluded that the error performance of the FL scheme is much higher.

6) HYBRID MODELS

It is possible to integrate two or more of these AI models and form a more robust model. Examples include combining RL and deep learning for RSMA optimisation [58], the use of GNNs [59] for large-scale RSMA systems, leveraging RL with the deep deterministic policy gradient (DDPG) algorithm [60], and RL with GNNs [61] or convolutional networks [62] for scalable and context-sensitive RSMA optimisation. Predictive analytics can be integrated with RL [63] to dynamically route, optimise routing, and eventually improve resource utilisation and network performance.

Table 3 shows the different applications of AI in RSMA-based 6G networks.

V. RF-EMF EXPOSURE AND QoS TRADE-OFFS IN RSMA-6G NETWORKS

The 6G wireless networks promise unprecedented data rates, ultralow latency, and dense connectivity; these will bring about an increase in signal transmissions and proliferation of network devices and base stations. Rapid densification in the deployment of energy-transmitting equipment (owing to higher operating frequencies and smaller coverage areas) has raised serious concerns about human exposure to RF-EMF. RSMA is designed to optimise spectrum usage and network efficiency in the proposed 6G networks. There is a need to understand the concept of RF-EMF, its impact on human health, mitigation strategies, and the benefits in QoS trade-off with RF-EMF exposure levels in the context of 6G networks.

A. UNDERSTANDING RF-EMF EXPOSURE

The electromagnetic frequency (EMF) spectrum ranges along a significant band of frequencies, which includes radio frequencies (RFs). The radiation emitted from the EMF spectrum can be categorised as ionising and non-ionising radiation [64]. RF-EMF has been established to be non-ionising radiation [65], [66]. However, as spectrum usage shifts to millimeter wave (mmWave), RF-EMF emission stimulates heat in human body tissues and thus increases the probability of RF-EMF radiation exposure [67]. The short wavelength and the low energy level of the mmWave band necessitate minimum heat inducement.

Green networks have been a major research area globally. Many researchers have explored this study [67], [68], [69], [70], addressing concerns about RF-EMF radiation exposure; using measurement, computation, and heuristic optimisation methods to analyse, address, and mitigate the challenge. With the introduction of 6G networks, more attention is drawn to how green this network would be. It is expected that 6G would make wireless communications attain lower RF-EMF and less health hazards by transmitting with near zero power consumption. Therefore, it is important to design an effective AI scheme with low complexity for 6G networks [3].

RF-EMF exposure is typically assessed using metrics such as the specific absorption rate (SAR), power density (PD), and exposure index (EI). These are expressions in terms of the electric field and/or magnetic field components. SAR measures the quantity of RF energy a unit mass of tissue absorbed, and it is measured in watts per kilogram (W/kg). PD is measured in watts per square meter (W/m^2), while EI is a ratio of SAR assessed to SAR maximum limit over a period [71]. PD is usually used for radiation at higher frequencies.

The 6G networks are expected to operate in the mmWave (3GHz – 300GHz) spectrum currently used by 5G networks. 6G networks will also exploit the optical wireless communication (OWC) band, including visible light communication (VLC) [1], [3], a spectrum regarded good for green networks due to its zero emission of RF-EMF radiation. In addition, the 6G network is expected to have a potential band called integrated satellite-terrestrial networks (ISTN), comprising terrestrial bands and a higher non-terrestrial spectrum [72]. The Federal Communications Commission (FCC) recently released the THz (0.1THz - 10THz) frequency band in the United States (US). Thus, it is anticipated that 6G networks will operate within this spectrum [3].

With these high operating frequencies, the wavelengths are shorter with lower energy levels that will necessitate minimum heat inducement. However, the 6G RSMA systems will be denser and more prolificated with increased antenna elements (massive MIMO) and beamforming. These amplify concerns about localised and aggregated RF exposure.

B. IMPACT OF 6G RF-EMF ON HUMAN HEALTH

The impact of RF-EMF on the health of 6G network users can be evaluated and analysed by computing the EI on network users using a simulated radiated power model, as illustrated in Fig. 3. Multiple users are randomly deployed in the RSMA-6G network system, with users exposed to RF-EMF radiation in the network due to the ownership of several

UEs that transmit and receive signals from APs. The spectral power density is expressed using the cross-sectional area, the transmitted power, and the antenna gain $G_k^A P$ as [68]

$$S_k = \frac{P_k G_k^{AP}}{4\pi d_k^{AP}}, \tag{12}$$

where d_k^{AP} is the distance between the AP and the UE. The electric field strength E_k of the RF-EMF is expressed as [73]

$$E_k = \sqrt{\eta_o * S_k}, \tag{13}$$

where η_o is the characteristic impedance of the free space. The SAR is evaluated using the electrical conductivity σ of tissue per tissue density ρ as [73]

$$SAR_k = |E_k|^2 * \frac{\sigma}{\rho}. \tag{14}$$

Using an average time of 6 minutes that reflect realistic usage and align with international health and safety standards [65] that account for thermal accumulation in tissues [66], the SAR limits and the evaluated SAR, the EI is evaluated as [73]

$$EI_k = \frac{SAR_k}{SAR_{limit}}. \tag{15}$$

The impact of RF-EMF can be analysed and compared to the standard thresholds set by regulatory bodies such as the International Commission on Non-Ionising Radiation Protection (ICNIRP) [65], IEEE [66], and FCC [74] in the US.

C. REGULATORY GUIDELINES

Despite being a non-ionising radiation, regulatory bodies such as the ICNIRP, the FCC in the US, and the IEEE have published safety guidelines and ensuring the protection of humans from high-intensity exposures and other potential hazards associated with RF-EMFs.

The ICNIRP, released updated exposure guidelines in 2020 [65], a global reference for exposure limits in frequencies ranging from 100 kHz to 300 GHz. As discussed, 6G networks will operate in the mmWave and THz spectrums. Therefore, our focus in these guidelines is on thresholds above 6 GHz operating frequencies. PD limits were updated to 10 W/m^2 and 50 W/m^2 for the general public and occupational exposure, respectively, averaged over 6 minutes for continuous exposures. The local SAR is 2 W/kg for the head and trunk, averaged over 10g of tissue, and 4 W/kg for the limbs.

The FCC adopts similar but stricter exposure thresholds and ensures compliance for network infrastructure and UE. Although they only have jurisdiction in the US, many countries have adopted these sterner thresholds of local SAR is 1.6 W/kg averaged over 1g of tissue, and maximum permissible exposure (MPE) of 1.0 mW/cm^2 (equivalent to 10 W/m^2) at frequencies between 1.5 GHz and 100 GHz for far-field exposure [64].

The IEEE in a detailed and widely referenced guideline IEEE Std C95.1-2019 [66], provides thresholds for safe human RF-EMF exposure. They stated the PD limit as 10 W/m^2, averaged over 6 minutes for far-field exposure above 6 GHz. The SAR limits are 10 W/kg over 10g of tissue (localised head/trunk), 2 W/kg over 10g of tissue, and 0.08 W/kg (general public) for occupational, general public, and whole-body average, respectively.

TABLE 4. RF-exposure regulatory limits.

Regulatory body	Metric	General public limit	Occupational limit
ICNIRP	SAR (10g)	2 W/kg	10 W/kg
	PD (>6 GHz)	10 W/m²	50 W/m²
FCC	SAR (1g)	1.6 W/kg	-
	PD	10 W/m²	-
IEEE	SAR (10g)	2 W/kg	10 W/kg
	Whole body SAR	0.08 W/kg	0.4 W/kg

These standards are summarised in Table 4 and are designed to prevent thermal effects such as tissue heating. AI-based RSMA-6G networks have the capability to optimise signals and high-gain beamforming with PD limits, especially when beams are steered dynamically. Therefore, AI-based optimisation must integrate exposure-aware constraints to ensure regulatory compliance during real-time adaptations.

D. STRATEGIES FOR RF-EMF REDUCTION IN RSMA

RF-EMF studies increased tremendously after the deployment of the 5G network in early 2020 due to the controversies around the newly deployed network and COVID-19. In addition to the controversies, there is a need to analyse, compute, compare, and mitigate radiation emissions in wireless networks.

The authors in [75] computed and compared the RF-EMF emitted in the UL and DL of the 4G and 5G networks. Their results showed that the 5G networks are safe and that the SAR and EI of users are below the limits. The results also showed that there are more concerns with the UE in the UL than with the APs in the DL system.

Similarly, the authors in [68] minimised the computed RF-EMF radiation emissions in [75]. They proposed a power control scheme that minimised the EI of the users subject to transmit powers, interference limits, and the required QoS (data rate) limits. Performance analyses showed that the scheme outperformed other schemes by providing the required QoS, reduced interference, and reduced RF-EMF radiation emissions.

The authors in [67] evaluated the effect of radiation emissions, data rate, and coverage ratio of a distributed basestation (DBS) network in the mmWave frequency band. The authors concluded that a DBS offers the best option compared to a centralised system in the mmWave band, as the DBS network mitigates radiation emissions and improves throughput.

Furthermore, the authors in [76] proposed a model for beam steering and a grid of beam antennas against the usual power extrapolation methods. The model focused on power

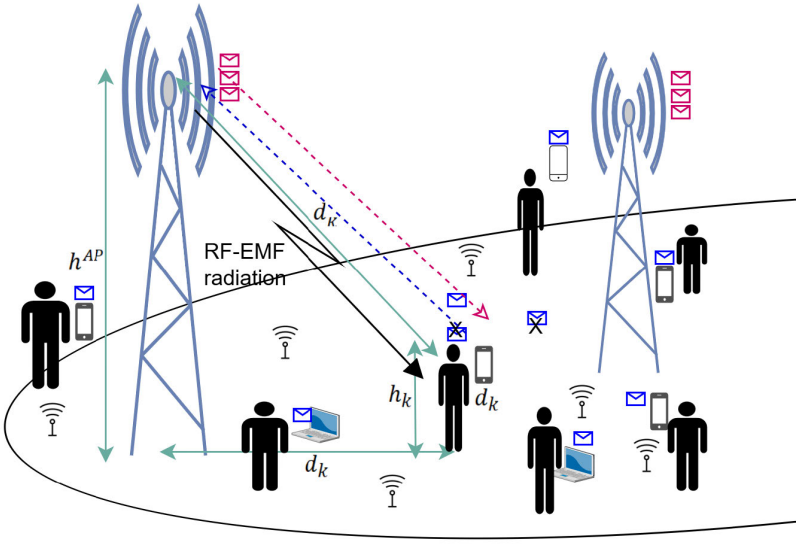


FIGURE 3. Radiated power model (QoS vs. network challenges).

reduction estimation using a simple approach to determine the average power density of the RF-EMF to determine approximate values of RF-EMF exposure in the 5G network and the NGN.

Clerckx et al. [21] highlighted how RSMA improves both spectral and energy efficiencies using user scheduling and beamforming optimisation which potentially reduces RF-EMF emissions. However, this optimisation can also affect the RF-EMF emissions, especially in wearable applications or indoors, through the concentration of energy in certain directions and areas.

Most works in the literature considered the use of heuristic and genetic algorithms in minimising RF-EMF exposure in wireless networks. AI through an efficient ML algorithm would be critical in assessing, monitoring, and controlling RF-EMF radiation from the networks, especially RSMA-6G networks. To do this, an ML algorithm (supervised, unsupervised, or reinforcement-based) is needed to optimise network parameters, balancing RF-EMF exposure minimisation with QoS requirements and network resource maximisation.

1) ML-BASED PREDICTIVE MODELS

ML techniques are powerful tools for forecasting RF exposure patterns and enabling proactive adjustments in transmission behaviour. These models perform learning using previous powers, allocated data, CSI, and user mobility to predict the likely RF-EMF zones, infer spatial radiation exposure patterns, and adjust the RSMA-6G system parameters accordingly. Maher et al. [77] showed that agents in ML-based RSMA systems can dynamically adjust the beam directions and reduce power to high-exposure hotspots without compromising the required SINR.

Similarly, federated learning [57] can be used to decentralise the exposure forecast while protecting data and preserving users' privacy.

2) BEAMFORMING OPTIMISATION FOR REDUCED RF-EMF EXPOSURE

Exposure-aware beamforming models can be designed to minimise RF-EMF exposure by optimising beamforming patterns and reducing unnecessary energy transmission [78], [79]. This approach can be achieved by considering metrics such as SAR and power density, in addition to traditional SINR objectives. For instance, researchers in [41] and [80] have proposed RF-aware beamforming algorithms that steer nulls towards sensitive regions, effectively minimising exposure while maintaining link reliability.

3) ENERGY-EFFICIENT TRANSMISSION SCHEMES FOR RSMA

Energy-efficient RSMA schemes aim to minimise total transmitted power while satisfying QoS requirements. These schemes involve power minimisation subject to constraints such as SINR, interference, and exposure limits. By reducing transmitted power, energy-efficient transmission schemes can decrease RF-EMF exposure and network interference [68]. Compared to NOMA and OMA, RSMA reduces redundant transmissions by preferentially assigning power to common streams decoded by all users [31]. Furthermore, integrating AI with RSMA optimisation, using EE as the objective function [59], [81], can effectively reduce RF-EMF exposure without compromising users' QoS.

E. TRADE-OFF BETWEEN RF-EMF REDUCTION AND QoS

Reducing RF-EMF exposure of users in the network often requires lowered power transmission, fewer antenna usage,

and dynamic beamforming which may lead to reduced network performance [82], [83]. However, unrestrained improvement of QoS can increase RF-EMF exposure of users in the networks. This brings about a complex trade-off that must be balanced to achieve both goals.

1) IMPACT ON DATA RATES, LATENCY, AND RELIABILITY

Efforts to reduce RF-EMF exposure can inadvertently affect QoS metrics such as data rates, latency, reliability, and connectivity [73], [78]. For example, lowering transmit power or widening the beam nulls to reduce exposure can decrease the SINR, leading to slower throughput and higher packet error rates. Similarly, limiting the use of high-frequency spectrum (e.g., mmWave) due to its elevated RF-EMF risks can restrict available bandwidth and increase latency [10]. Studies [41], [84] showed how to achieve balance with network performance and some network challenges, such as interference, latency, radiation exposure, under low allocated power. This can be achieved by setting the objective function alongside the constraints and using dynamic beam steering [41], which can increase latency due to reconfiguration delays.

2) OPTIMISATION FRAMEWORKS USING PARETO-BASED ML MODELS

Pareto-optimal multi-objective optimisation frameworks seek to find non-dominated solutions where no single objective (in this case, the data rate or RF exposure) can be improved without compromising another. To balance QoS with RF-EMF exposure, researchers use Pareto-based ML models such as RL and evolutionary algorithms (EA). Niu et al. [82] proposed a two-stage RSMA optimisation scheme where the resource efficiency (RE) metric is defined as the desirable trade-off between EE and SE and optimised to improve RE. Pareto Q-learning and NSGA-II-based evolutionary models have also been used to dynamically tune RSMA parameters based on user sensitivity to RF-EMF [85]. These methods provide scalable and real-time solutions for exposure-sensitive communication. Furthermore, the introduction of meta-learning brings about varying constraints and faster convergence.

VI. PERFORMANCE EVALUATION OF RSMA IN 6G NETWORKS

A. SIMULATION FRAMEWORKS

Performance evaluation of RSMA in 6G networks requires a robust and realistic simulation framework that replicates the complex dynamics of wireless channels, user mobility, challenges, and power constraints. MATLAB [6], Python [86], QUAsi Deterministic RadIo Channel GenerAtor (QuaDRiGa) [87], [88], and NS-3 [89] are the most used tools, offering flexibility for physical layer simulation, integration of AI algorithm, signal transmission simulation, and network-level modelling respectively. RSMA systems are typically modelled with different modulation concepts (such as BPSK and QPSK) [25], [26], [27], [28], [90], adaptive power allocation [91], and multi-user MIMO scenarios [87]. Integration with AI algorithms such as reinforcement learning allows for optimisation across multiple metrics, including RF-EMF exposure.

Simulation environments typically incorporate realistic channel models, including stochastic Rayleigh or Rician fading [86], [92], [93], path loss models [67], and scheduling schemes [91]. To evaluate the performance of RSMA under practical 6G conditions, simulations often implement dynamic spectrum access, rate-splitting encoding [86], [92], [93], SIC decoding [90], and exposure-aware beamforming [41]. These simulations enable the study of trade-offs and potential gains offered by RSMA.

B. PERFORMANCE METRICS

Several performance metrics are considered when evaluating RSMA systems in 6G networks. These metrics provide insight into system efficiency and reliability, environmental factors, user experience, and network impact on user health.

1) SPECTRAL EFFICIENCY

SE (bits/s/Hz) reflects how effectively the available bandwidth is utilised. RSMA's ability to superpose and decode signals using SIC makes it highly spectrally efficient, especially in scenarios with imperfect CSI. Studies show that RSMA consistently outperforms NOMA and OMA in SE under varying channel conditions [93]. The authors in [87] evaluated and compared RSMA with SDMA in 6G networks under low and high spatial correlation conditions using SE as a metric. The authors concluded that varying the number of antennas affects the SE in the RSMA system; however, it still outperforms the SDMA

2) ENERGY EFFICIENCY

EE, measured in bits/Joule, is a key performance metric for RSMA in 6G networks. The inherent flexibility in RSMA's power distribution between private and common streams optimises energy consumption. Furthermore, integrating AI with RSMA could enable dynamic power control, allocating resources based on real-time user demand and CSI. A study in [81] demonstrated the effectiveness of this approach, showing that the RSMA-DRL scheme achieved higher EE compared to SDMA-DRL and other multiple access schemes.

3) BIT ERROR RATE

The bit error rate (BER) is a critical metric that measures the rate of bit errors in transmission, influenced by modulation schemes, coding techniques, and decoding accuracy. RSMA may employ advanced coding techniques, such as LDPC and polar codes [24], to minimize BER even in dense multi-user environments. Additionally, RSMA's successive decoding concept provides robustness against noise and interference. A study in [25] evaluated the performance of a proposed

RSMA scheme using BER as a metric, demonstrating close alignment between analytical and numerical results.

4) LATENCY

Latency in RSMA systems is affected by factors such as decoding complexity, queue management, and scheduling [6]. Although SIC introduces some delays, RSMA can maintain low latency by optimally distributing decoding responsibilities. Real-time adaptive modulation and coding (AMC), along with efficient scheduling policies, are essential for achieving ultra-reliable low-latency communication (URLLC) in RSMA. The authors in [6] evaluated the complexity and latency in the proposed resource allocation algorithm that minimises the maximum transmission latency for uplink RSMA and compared the performance with NOMA. Their results show that the RSMA outperformed the benchmarked MA schemes in terms of latency and complexity.

5) RF-EMF EXPOSURE

RF-EMF exposure can be evaluated using metrics such as SAR, PD, and EI. RSMA's flexible transmission framework enables exposure-centric optimisation, including reducing power in sensitive areas or minimising beam exposure duration. AI-based models are increasingly used to manage this trade-off, offering a real-time exposure minimisation while maintaining the required quality of service such as date rate, SINR, and SNR [69].

C. BENCHMARKING RSMA VERSUS OMA VERSUS NOMA

In several works in the literature, other MA techniques were used to benchmark the proposed RSMA techniques. Table 5 shows some of the works that compared RSMA with OMA, NOMA, or SDMA evaluated with the performance metrics (such as spectral efficiency, energy efficiency, BER, latency and RF-EMF exposure) that were discussed in Section VI-B.

VII. OPEN CHALLENGES & FUTURE RESEARCH DIRECTIONS

Several areas require further research and development in AI-RSMA-based 6G networks, including hardware/architecture, software, integration, operation, safety, implementation, and evaluation.

A. SCALABILITY

With the massive connectivity expected in the integrated RSMA-6G networks, scalability becomes a major concern. Managing user clustering, interference, and dynamic rate-splitting among the several users would lead to increased computational complexity. Furthermore, the RSMA decoding mechanism is based on SIC and must be scalable for the connected UE to achieve minimal latency. Future research should focus on scalable algorithms, hierarchical clustering, and decentralised optimisation [97], [98] for large-scale RSMA networks.

TABLE 5. Benchmarked RSMA technique and other MA techniques.

Ref.	RSMA	OMA	NOMA	SDMA
Yu et al. [32]	✓	×	✓	✓
Yang et al. [33]	✓	✓	✓	×
Xu et al. [8]	✓	×	✓	×
Arora & Jaiswal [30]	✓	×	✓	×
Li et al. [9]	✓	✓	×	×
Huang et al. [81]	✓	✓	×	✓
Chen et al. [59]	✓	×	✓	×
Hu et al. [6]	✓	×	✓	×
X. Li et al. [93]	✓	✓	×	×
Taskooh et al. [86]	✓	✓	✓	×
Chrysologou et al. [92]	✓	✓	×	×
Zha et al. [25]	✓	×	×	✓
Pokamestov et al. [87]	✓	×	×	✓
Zhang et al. [94]	✓	✓	✓	×
H. Lu et al. [91]	✓	✓	✓	×
H. Li et al. [11]	✓	×	✓	✓
Kowshik et al. [27]	✓	✓	✓	×
Jafarkhani et al. [28]	✓	✓	✓	×
Hieu et al. [95]	✓	×	×	✓
Q. Liu et al. [96]	✓	×	✓	×

B. REAL-TIME AI DEPLOYMENT

Although AI-based optimisation techniques have shown promise in managing RSMA parameters, their real-time deployment remains a challenge. Training deep learning models requires large datasets and computational resources that may not be available at the network edge. In addition, inference latency, model drift, and online learning robustness need to be addressed for AI to function reliably in real-time RSMA systems. Lightweight and adaptive AI models such as federated learning [38], edge inference engines [99], and few-shot learning [100], [101] approaches are emerging as potential solutions.

C. SECURITY AND PRIVACY

In RSMA-enabled 6G networks, the roles of AI models in beamforming, power assignment, resource allocation, exposure control, training data security, and user information become crucial [20]. AI-driven systems are vulnerable to adversarial attacks, model poisoning, and inference attacks. Furthermore, exposure-aware adaptation of RSMA may inadvertently reveal sensitive user location or health information. Privacy-preserving machine learning (PPML) [102], [103], homomorphic encryption [104], and secure federated learning [40] will play a vital role in mitigating these threats.

D. POWER ALLOCATION UNDER RF-EMF CONSTRAINTS

Balancing QoS requirements with RF-EMF safety thresholds [73], [83] in real time is computationally intensive. Power allocation strategies [105] that reduce RF-EMF exposure must not compromise the performance of users with poor channel conditions.

E. HYBRID MA MODELS

Hybrid MA strategies [106], [107], [108], [109] that combine RSMA with other access technologies such as NOMA,

OMA, and SDMA are being considered to improve flexibility and performance in dynamic 6G environments. The challenge lies in developing frameworks that can integrate or dynamically switch between these MA techniques adaptively based on network conditions, user capabilities, and RF-EMF constraints. Research is ongoing into hybrid models that leverage RSMA's rate-splitting benefits while achieving backward compatibility with existing MA standards. The authors in [109] proposed and investigated a hybrid RSMA-NOMA; their numerical results showed the trade-offs and better performance of the hybrid RSMA-NOMA in terms of fairness, throughput, and complexity.

F. RSMA INTEGRATION WITH AI MODELS

Although AI techniques are promising, training robust, generalisable models across diverse network conditions is still an active area of research. There are challenges [110] in model interpretability, convergence, and complexity [111], cost [112], privacy, security [113], hardware constraints [19], and real-time responsiveness for AI agents controlling RSMA parameters.

G. FUTURE RESEARCH DIRECTIONS

Research should focus on hardware-aware RSMA designs, leveraging low-complexity encoding/decoding mechanisms such as hardware-friendly Polar codes and hybrid analog-digital processing. Future RSMA networks could use AI-driven self-optimising models such as federated learning, meta-learning, and deep reinforcement learning to self-adapt in real-time to user distribution, QoS demand, and EMF exposure levels. Research is required on the development of a multi-objective Pareto-optimal optimisation frameworks (for QoS-EMF Trade-Off) that simultaneously target spectral efficiency, energy efficiency, power minimisation, and RF exposure thresholds across multiple users and cells.

In managing RF-EMF in dense urban areas, research should be directed toward joint design and optimisation of RSMA and intelligent reflecting surfaces (IRS), which can intelligently redirect signals to reduce direct exposure and enhance signal strength. Future research must contribute to analysing and verifying RF-EMF exposures in RSMA-based 6G systems. In addition, exposure-aware mitigation and optimisation schemes should be developed and validated for 6G networks. Research can also include the integration of exposure monitoring sensors into RSMA testbeds and small cells, which can help to track and report exposure in real time.

VIII. CONCLUSION

This survey underscores the transformative role of RSMA combined with AI in 6G networks. RSMA's ability to flexibly manage interference, when enhanced by AI-driven optimisation, offers promising improvements in QoS and controlled RF-EMF exposure. As 6G networks become reality, intelligent, scalable, and safe communication systems will depend on such integrated approaches. Future research must address implementation challenges, privacy, and ethical considerations to fully realise these benefits.

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