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SURVEY

ML-Based Radio Resource Management in 5G and Beyond Networks: A Survey

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ABSTRACT In this survey, a comprehensive study is provided, regarding the use of machine learning (ML) algorithms for effective resource management in fifth-generation and beyond (5G/B5G) wireless cellular networks. The ever-increasing user requirements, their diverse nature in terms of performance metrics and the use of various novel technologies, such as millimeter wave transmission, massive multiple-input-multiple-output configurations and non-orthogonal multiple access, render the multi-constraint nature of the radio resource management (RRM) problem. In this context, ML and mobile edge computing (MEC) constitute a promising framework to provide improved quality of service (QoS) for end users, since they can relax the RMM-associated computational burden. In our work, a state-of-the-art analysis of ML-based RRM algorithms, categorized in terms of learning type and potential applications as well as MEC implementations,is presented, to define the best-performing solutions for various RRM sub-problems. To demonstrate the capabilities and efficiency of ML-based algorithms in RRM, we apply and compare different ML approaches for throughput prediction, as an indicative RRM task. We investigate the problem, either as a classification or as a regression one, using the corresponding metrics in each occasion. Finally, open issues, challenges and limitations concerning AI/ML approaches in RRM for 5G and B5G networks, are discussed in detail.

INDEX TERMS 5G, B5G, deep learning, machine learning, mobile edge computing, radio resource management.

ACRONYMS

3GPP	Third Generation Partnership Project.
4G	4th Generation.
5G	5th Generation.
6G	6th Generation.
ABC	Artificial Bee Colony.
AI	Artificial Intelligence.
AM	Amplitude Modulation.
ANN	Artificial Neural Networks.
B5G	Beyond 5th Generation.
BBU	Baseband Processing Unit.
BER	Bit Error Rate.
BP	Blocking Probability.
BS	Base Station.
CDMA	Code Division Multiple Access.
CIR	Channel Impulse Response.
CN	Core Network.
CNN	Convolutional Neural Network.
CRAN	Cloud RAN.
CSI	Channel State Information.
D2D	Device-to-Device.
DL	Deep Learning.
DL/UL	Down/Up Link.
DNN	Deep Neural Networks.
EE	Energy Efficiency.
EMF	Electromagnetic Field.

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eMBB	Enhanced Mobile Broadband.
ETSI	European Telecommunications Standards Institute.
FC	Femto-Cell.
FL	Federated Learning.
FM	Frequency Modulation.
FR	Frequency Range.
gNodeB	Next Generation Node B.
H2H	Human-to-Human.
HetNets	Heterogenous Networks.
IoT	Internet of Things.
IP	Internet Protocol.
ITU	International Telecommunication Union.
k-NN	k-Nearest Neighbors.
LTE	Long Term Evolution.
M2M	Machine-to-Machine.
MA	Margin Adaptive.
MARL	Multi-Agent Reinforcement Learning.
MCTS	Monte Carlo Tree Search.
MEC	Mobile Edge Computing.
MIMO	Multiple-Input-Multiple-Output.
MINLP	Mixed Integer Non-linear Programming.
ML	Machine Learning.
MOS	Mean Opinion Score.
mMTC	Massive Machine-Type Communications.
mmWave	Millimeter Wave.
m-MIMO	Massive MIMO.
MNOs	Mobile Network Operators.
MU-MIMO	Multi-User MIMO.
MTC	Mobile Type Communications.
NLP	Natural Language Processing.
NOMA	Non-Orthogonal Multiple Access.
non-IID	Non-Independent and Identical Distribution.
NP	Non-Deterministic Polynomial-Time.
NR	New Radio.
OFDM	Orthogonal Frequency Division Multiplexing.
OFDMA	Orthogonal Frequency Division Multiple Access.
O-RAN	Open Radio Access Network.
OTA	Over-the-Air.
P2P	Point-to-Point.
PF	Proportional Fairness.
PRB	Physical Resource Block.
QoE	Quality of Experience.
QoS	Quality of Service.
QPSK	Quadrature Phase Shift Keying.
RA	Rate Adaptive.
RAN	Radio Access Network.
RAT	Radio Access Technology.
RB	Resource Block.
RF	Radio Frequency.
RL	Reinforcement Learning.
RMSE	Root Mean Square Error.
RN	Relay Nodes.
RRM	Radio Resource Management.
RSRQ	Reference Signal Received Quality.
RSRP	Reference Signal Received Power.
RSSI	Received Signal Strength Indicator.
SE	Spectral Efficiency.
SNR	Signal-to-Noise-Ratio.
SON	Self-Organizing Network.
SU-MIMO	Single-User MIMO.
SVM	Support Vector Machines.
TDMA	Time Division Multiple Access.
UAVs	Unmanned Aerial Vehicles.
UE	User Equipment.
UHF	Ultra High Frequency Band.
URLLC	Ultra-Reliable-Low-Latency Communication.
V2M	Vehicle-to-Machine.
V2V	Vehicle-to-Vehicle.
WMMSE	Weighted Minimum Mean Squared Error.
WWWW	World-Wide-Wireless-Web.

I. INTRODUCTION

A. THE EMERGING ROLE OF MACHINE LEARNING IN 5G

The development of fifth-generation (5G) broadband wireless networks has been nowadays significantly accelerated and is worldwide at the stage of installation and implementation of the backbone network [1], [2]. Moreover, mobile network operators (MNOs) gradually launch in the market terminal devices (mobile phones, boards, etc.) that support 5G networks. According to the studies in [3], [4], the monthly data demand will reach 100 exabytes with about 31.6 billion active devices by 2023, thus doubling the current requirements. Similar to [3], an updated whitepaper from CISCO is expected within 2022, also predicting increased data demand until 2024. In this context, the necessity for optimal solutions, in terms of network management and allocation of available radio resources, is apparent.

It is already visible that 5G acts as an integrator for diverse applications and services. To this end, 5G networks utilize vehicular communications [5], device-to-device (D2D) communications [6], machine-to-machine (M2M) communications [7], mobile edge computing (MEC) [8], cloud computing [9] and internet of things (IoT) [10], in order to meet the needs for enhanced mobile broadband (eMBB), massive machine-type communications (mMTC) and ultra-reliable-low-latency-communications (URLLC) [11].

More specifically, the authors in [12], [13] summarize the key components and innovations incorporated in 5G networks, as: a) Modern approaches in radio-link management, such as open radio access network (O-RAN) and virtual networks, in order to meet the strict criteria of latency, capacity and data traffic in 5G transmission, b) Extended coverage, which includes the installation of multi-nodes and multi-antennas in the network's coverage area, in order to use multi-hop techniques for fast handovers through service cells and base stations (BSs), c) Service-based network dimensioning, which utilizes the self-generated channel state information (CSI), in order to meet the enhanced URLLC criteria. Cell and BS planning should follow even stricter requirements to support new usage scenarios and applications (smart cities, IoT, emergency alerts). Thus, heuristic approaches, based on data analysis and machine learning (ML), are proposed in network dimensioning [14] and d) Use of new frequency bands, which includes the extended operating spectrum band and the new spectrum regimes [15].

In addition, 5G and B5G networks extend the deployment of technologies that were introduced in fourth-generation (4G) networks and also encapsulate new ones (see also Fig. 1). These include massive multiple-input-multiple-output (m-MIMO) configurations [16], millimeter wave (mmWave) transmission [17], network slicing [18], relay nodes (RNs) [19] and non-orthogonal multiple access (NOMA) [20]. However, the coexistence of these technologies can significantly increase network complexity, due to the insertion of multiple computational levels and hardware needs, thus necessitating the importance of optimal radio resource management (RRM) strategies [21]. For example, accurate CSI is required for the effective deployment of m-MIMO architectures and NOMA schemes. This, in turn, increases the overall signaling burden, due to the increased number of pilot signals. Moreover, in typical MIMO configurations, each antenna is connected to a separate radio frequency (RF) chain, thus supporting a fully digital (FD) beamforming approach. However, in an m-MIMO case, this would be prohibitive, as it would significantly increase hardware complexity. Hence, suboptimal techniques are proposed in the literature, based on a hybrid analog-digital beamforming approach [22].

It is, therefore, understood, that a tradeoff between optimal network goals and computational complexity can only be achieved through an efficient RRM. Until now, the allocation decisions were made continuously in each timeslot, based on local network conditions and the data traffic load to be serviced. However, the aforementioned enhanced requirements of 5G networks raise the need for, if not require, a decentralized and intelligent data management system, that can support flexible RRM decisions. In this direction, the utilization of data offered by ML and the features extracted by the corresponding algorithms can effectively contribute to fast RRM responses [23], [24].

The current research interest in incorporating ML techniques in 5G networks is mainly focused on the core network (CN) [25]–[27] (indicatively: traffic forecasting [28], [29], network slicing [30], privacy and security [31], etc.). Lately, ML models are introduced in RAN and the development of artificial intelligence (AI) and ML-based RRM algorithms has attracted scientific interest, as well (e.g. [32]–[35]; an exhaustive analysis of ML-based schemes in 5G and B5G RAN, focusing on RRM, is presented in section III).

The scope of this survey paper is to summarize recent works in the field of ML-based RRM, categorize them based on the implemented ML technique, and thus provide guidelines to researchers for selecting the suitable category of ML algorithm in each RRM sub-problem and highlight open issues, limitations and potential solutions. This is achieved through a state-of-the-art analysis of the existing literature, focusing on the performance of each proposed ML-algorithm with respect to various networks' key performance indicators (KPIs). Moreover, in an effort to determine the capabilities that ML methods bring to RRM-related tasks, the problem of throughput prediction is investigated, as an indicative case of ML utilization in 5G/B5G networks, by comparing various ML algorithms.

B. RELATED SURVEYS–PAPER OVERVIEW

The emerging need for efficient RRM through ML, that is presented in the previous sub-section, has motivated many researchers over the last years. The studied surveys in this subsection, have focused on ML deployment for effective resource allocation strategies' definition in 5G/B5G networks. Table 1 summarizes these surveys, presenting the key problems and the corresponding contributions.

In [37], the authors considered ML, data analytics and natural language processing (NLP) in network planning and management of 5G networks, with emphasis on RRM and security issues. Moreover, a prediction of the channel impulse response (CIR) problem was presented as an indicative use case. The authors in [38] presented a state-of-the-art approach in energy-aware 5G systems. In this framework, ML-based solutions were investigated in practical Third Generation Partnership Project (3GPP) new radio (NR) features, in order to maximize energy efficiency (EE). According to the presented analysis, reinforcement learning (RL) techniques are more suitable in environments with multiple constraints.The significance of deploying Green AI techniques, in order to reduce power consumption in wireless networks, is highlighted, as well. In [39], the authors focused on the significance of RRM through ML in the development of sixth-generation (6G) networks. In this context, the extensive usage of mobile devices and the dynamic changes in CSI and data traffic formulate a multi-dimensional quality of service (QoS) problem. Therefore, the authors suggested that power allocation and channel modeling should become data-driven through ML models. In addition, they proposed that the existing ML schemes should consider data reduction methods in the training phase, as networks' datasets are characterized by large amounts of data and features. Finally, the significance of a trade-off between supported services (e.g., augmented and virtual reality (AR/VR) for 6G networks) and the strict requirements for latency, power, privacy, security and QoS, is highlighted, as well.

The authors in [40] present an overview of the existing RRM techniques in 5G/B5G networks. In this context, the utilization of game theory, heuristic mechanisms and ML are presented, along with all the related constraints (e.g., latency, QoS, EE). The main conclusion is that deep learning (DL) and RL approaches can accelerate the performance of 5G and B5G networks, due to their ability to quickly learn and cooperate with all the elements of the network's environment.

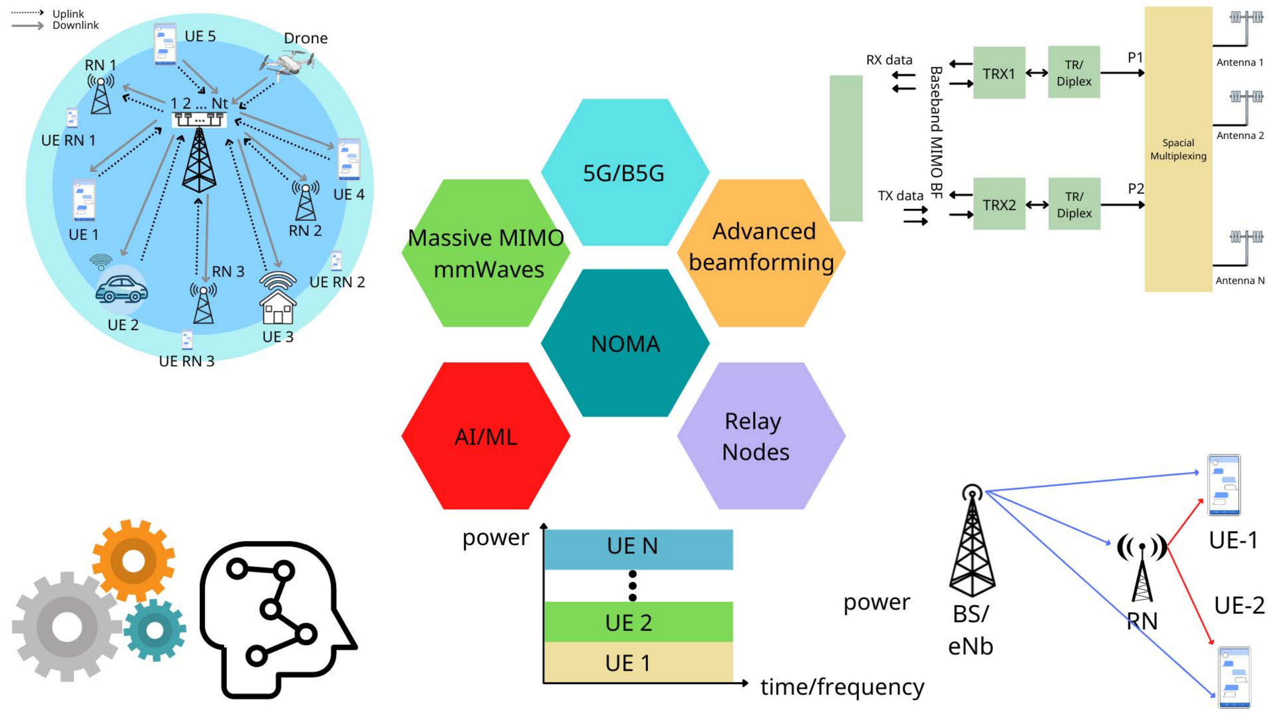

FIGURE 1. 5G/B5G networks enablers.

In the same context, the authors in [41] focus specifically on DL techniques. Thus, deep neural networks (DNNs) and convolutional NNs (CNNs) are investigated in the scope of resource allocation, security and channel estimation [27]. According to the conclusions drawn, there is an upcoming trend towards using DL in wireless networks, since B5G and 6G networks will integrate higher levels of intelligence through ML, in order to support reconfigurable technologies, such as terahertz communications and unmanned aerial vehicles (UAVs). Similarly, the authors in [42] investigated ML utilization in different computing scenarios, such as 5G, IoT, edge, fog, cloud and vehicular fog computing. Even though supervised, semi-supervised and unsupervised learning approaches are presented, the authors focus on DL ones providing a related taxonomy. They concluded that Deep RL approaches have the most efficient results in the resource allocation problem. However, data quality and hyperparameter tuning considerations are raised in order for better ML models to be implemented. Moreover, DL integration in AI-enabled ORAN architectures is investigated in [43]. The authors compared a DL solution based on edge support, virtualization control and management, as well as energy consumption. Furthermore, DL use cases and implementations are presented, leading to high-performance learning models. Finally, open issues on privacy and security, network slicing and energy consumption are analyzed, as well.

The authors in [44] presented an examination of distributed AI/ML approaches in next generation communication networks. More specifically, overhead reduction, resource distribution enhancement, privacy and security issues in a distributed ML environment are analyzed along with ML frameworks, based on up-to-date literature. The authors highlighted the need to improve computing hardware, cloud and edge servers in order to secure the efficient performance of algorithms, with respect to strict latency requirements, which occur in distributed computing wireless networks.

The authors in [31] introduce AI/ML as a set of techniques that can upgrade the performance of wireless networks, integrate new usage scenarios and enable emerging technologies. In this framework, an overview concerning ML-based solutions in physical layer aspects, channel modeling and measurements, network management and application layer, is provided. The authors conclude that the integration of AI/ML is still at an early stage, and standardization progress should be further accelerated.

The above-presented surveys describe some aspects of the current usage of AI/ML techniques in the resource management procedures of modern era wireless networks. Table 1 summarizes these surveys and their contributions. The first column states the area(s) of interest for each survey, the second column gives the specific RRM-related problems that are analyzed in each survey, and the last column presents contributions and suggestions that each survey provides. Our work is included, as well. However, the above-presented approaches, as it is also visible from Table 1, either focus on ML integration in multiple Open Systems Interconnection model layers [31], [37], [39] or on a specific category of ML algorithms for RRM [40]–[42], [44] or on a specific RRM related sub-problem [38], [43]. Our motivation is to extend

TABLE 1. Presentation of surveys in AI/ML for RRM.

Survey	*Area(s) of interest*	*Key RRM problems*	*Significant contributions, conclusions*
[37]	integration of AI and data analytics in the context of 5G	data acquisition; knowledge discovery in generating reliable CSI	comparison of CIR prediction techniques; need for fog distributed computing
[38]	energy efficient resource allocation optimization to achieve QoS	m-MIMO and ML role in minimization of power consumption	comparison of CIR prediction techniques; need for fog need for joint use of Green AI and network planning; multiuser MIMO channel modeling, renewable sources
[39]	types of Learning in 6G Networks (RAN and application level)	directions in using ML in resource management; power allocation and channel modelling	extensive use of AI/ML both in application and infrastructure level to meet increased requirements
[40]	game theory; heuristic mechanisms; ML in URLLC RRM	RRM as multiconstraint optimization problem with respect to QoS requirements	promotion of RL and DL approaches in RRM, due to their ability to quickly learn from the environment
[41]	DL in 5G/B5G Networks	DNNs in resource management; MIMO; security	use of DL and NOMA in RRM to optimally satisfy QoS requirements and limit bandwidth usage
[42]	ML and DL in various computing paradigms	RRM in the context of 5G, IoT, edge, fog, cloud, and vehicular fog computing	data quality considerations; hyperparameter tuning; need for contextual models design
[43]	DL in O-RAN architectures; deployment overview	spectrum management; Handover management	DL use cases presentation; privacy/security considerations in network slicing; energy concerns
[44]	Distributed ML for 5G/B5G (CN, RAN and application layer)	resource distributed optimization;client selection; physical link optimization	frameworks comparison; computing hardware, cloud and edge servers to secure software and algorithms' high-performance with respect to strict latency requirements.
[31]	overview of AI/ML usage in 5G CN, RAN and application layer	overview of existing approaches	ultra-fast training; need for distributed computation and standardization
Our Paper	ML algorithms in wireless networks' RRM	categorization of ML-based RRM solutions in terms of type of learning; user and subcarrier allocation; power and interference management according to KPIs	guidelines for selecting suitable category of ML algorithm; promotion of DL and MEC approaches in multi-goal RRM problems; limitations and open issues in ML-based RRM

these works and focus on all ML categories analyzing their impact and usability in a plethora of cellular networks' RRM sub-problems.

The key contribution of this paper is two-fold:

1) To present a state-of-the-art summary concerning ML-based RRM approaches. In this context, our interest is mainly focused on the categorization of the ML-based RMM schemes proposed in the literature, in terms of the type of learning, and, thus, on defining the optimal ML solution in various RRM sub-problems (KPIs prediction, user, subcarrier and power allocation, etc.), with respect to different network metrics (i.e., QoS, quality of experience (QoE), throughput, etc.). In order to achieve this, first, the general RRM problem is formulated, while significant non-ML approaches and their limitations are highlighted, as well. Then, the state-of-the-art concerning ML-based approaches in 5G/B5G RRM is presented. As already mentioned, these approaches are categorized by the type of ML models used by each one of them (Supervised, Unsupervised, Reinforcement). Furthermore, the coexistence of MEC and distributed learning techniques is analyzed, as it can tackle various challenges, especially concerning the training time of ML models.
2) Through the above procedure, representative conclusions are drawn, as far as which ML models are appropriate in each RRM related sub-problem, based on the network orientation. Moreover, limitations in current research efforts, open issues and discussion over the state-of-the art approaches are highlighted in an effort to both present potential solutions in these considerations and motivate future work on these fields. Thus, guidelines and research frameworks are proposed regarding AI/ML utilization for efficient resource allocation in 5G/B5G networks.

Finally, in order to highlight the significance of AI/ML implementation in RRM, the problem of throughput prediction is investigated, as an indicative RRM task, treated either as a classification or a regression problem. Various ML algorithms are considered, results are presented, and performance is evaluated, based on selected ML KPIs for

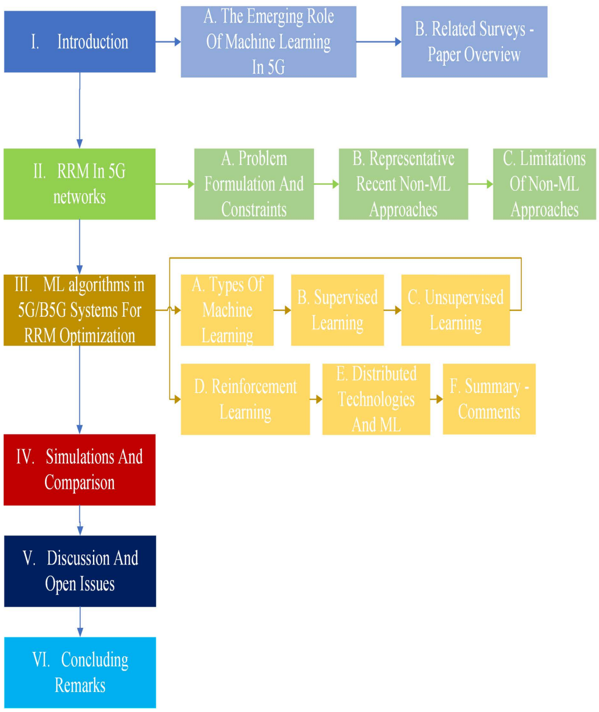

FIGURE 2. Paper structure.

each task. Finally, through the above-described analysis, limitations and open issues are witnessed and potential solutions are described.

The rest of this manuscript is organized as follows (see also Fig. 2): In Section II, the joint user, subcarrier and power allocation RRM problem is formulated, with respect to the corresponding constraints. Moreover, significant non-ML RRM works are presented and their limitations are highlighted. In Section III, the different types of ML are analyzed. In the same section, a state-of-the-art presentation, concerning AI/ML algorithms in 5G/B5G systems' RRM, is performed. The ML-based solutions are categorized by the type of learning. Furthermore, the joint employment of ML and distributed technologies (such as MEC) is presented and proposed as an efficient way to tackle the existing limitations. In Section IV, the employed ML algorithms for throughput prediction are presented, as well as the performance comparison among them. In Section V, open issues in the field of AI/ML in RRM are stated and suggestions for future works are drawn. Finally, concluding remarks are provided in Section VI.

II. RRM IN 5G NETWORKS

A. PROBLEM FORMULATION AND CONSTRAINTS

Even though RRM problem's criticality originates from the first steps of wireless and mobile communications, the significance of effectively managing the available radio resources was empowered during the 4G era, when the increase of data rates was accompanied by the high interference levels (especially co-channel). In the 4G, 5G and 6G era, RRM considers not only the allocation of physical resource blocks (PRB's) or subcarriers (typical subcarrier spacing is 600 kHz in frequency range 1 (FR1) of 5G and 2400 kHz in FR2) [15], [45], but also power management, scheduling, traffic control and handover management.

In general, RRM considers two main objectives, that in case can be treated as joint. The first one is power minimization, which is referred to as margin-adaptive (MA), while the latter is network efficiency maximization. In this framework throughput (or rate) maximization (rate adaptive - RA) is mainly considered. MA minimization considers overall and per user minimization of power consumption. Respectively, RA maximization takes into account overall and per user minimum throughput maximization [46]. Both approaches include a plethora of parameters, at cases mutually exclusive, that can significantly increase the complexity of RRM. In fact, in [45], the non-deterministic polynomial-time (NP)-hardness of the resource allocation problem is proved. Consequently, sub-optimal solutions are proposed.

In the 4G-LTE era, when OFDMA techniques were introduced, RRM algorithms mostly considered the maximization of users' throughput, based on QoS requirements, such as the key implementation criterion. The main categorization was the stage at which RRM was performed, considering sectors or BSs, with centralized or decentralized approaches. An innovative solution was introduced by game theory, where the RRM problem was treated as a game and each user as a player. Techniques such as Nash bargain (NBS), Hungarian NBS and Raiffa bargain (RBS) were the most common ones [47].

In a typical 5G MIMO cellular orientation, the total bandwidth, denoted as W, is divided into a predefined number of L subcarriers, which are allocated to users, according to their demands and overall constraints [48]. The system serves as many users as possible, till all subcarriers are allocated (N users). BSs are equipped with M_t transmitting antennas, while users are equipped with M_r receiving ones. The signal-to-noise-plus-interference-ratio (SNIR) for the n^{th} user ($1 \leq n \leq N$), associated with the l^{th} subcarrier ($1 \leq l \leq L$) for a specific channel realization and assuming independently transmitted streams among different users, is defined as follows [49]:

$$SNIR_{n,l} = \frac{G_{n,n,l}}{\mathbf{r}_{n,l}^{H}\mathbf{r}_{n,l}I_0 + \sum_{m \neq n, l \in S_m} G_{n,m,l}} \tag{1}$$

where $G_{n,m,l} = p_{n,l}\mathbf{t}_{m,l}^{H}\mathbf{H}_{n,sec(m),l}^{H}\mathbf{r}_{n,l}^{H}\mathbf{r}_{n,l}\mathbf{H}_{n,sec(m),l}\mathbf{t}_{m,l}$, $\mathbf{H}_{n,sec(n),l}$ represents the $M_r \times M_t$ channel matrix for the l^{th} subcarrier of the n^{th} user relevant to its serving sector, $\mathbf{t}_{n,l}$ is the $M_{\text{t}} \times 1$ transmission vector, assuming diversity combining transmission mode, $\mathbf{r}_{n,l}$ is the the Maximal Ratio Combing multiplying vector and $p_{n,l}$ denotes the transmission power allocated to the l^{th} subcarrier of the n^{th} user. Moreover, the set S_n indicates the subcarriers allocated to the n^{th} user and I_0 is the thermal noise level. Finally, $\mathbf{A}^H$ denotes the conjugate transpose of matrix $\mathbf{A}$. Thus, the achievable data rate on the l^{th} subcarrier is $r_{n,l} \leftarrow W \cdot log_2(SNIR_{n,l})$ [50], and the corresponding aggregate rate for the n^{th} user is $R_n \leftarrow \sum_{s\in S_n}^{N} r_{n,s}$. Then, the total throughput is given by:

$$R = \sum_{n=1}^{N} r_{n,s} \tag{2}$$

In most of the state-of-the-art RRM works, the target is to maximize EE, SE, Jain's fairness index (J) and, at the same time, minimize blocking probability. EE and SE are given by:

$$EE = \frac{R}{\sum_{n=1}^{N}\sum_{s\in S_n} p_{n,s}} \tag{3}$$

$$SE = \frac{R}{W} \tag{4}$$

Moreover, J index is defined as:

$$J = \frac{(\sum_{n=1}^{N}\sum_{s\in S_n} r_{n,s})^2}{N\cdot\sum_{n=1}^{N}\sum_{s\in S_n} r_{n,s}^2} \tag{5}$$

Finally, blocking probability (BP) is defined as the ratio of rejected users to the total number of used that tried to access the network.

The aforementioned optimization problem is subject to the following system constraints:

- $\sum_{s\in S_n} p_{n,l} \le p_{max}$, where p_{max} denotes the maximum power limit per user.
- $p_{n,l} \ge 0, 1 \le n \le N, 1 \le l \le L$, which demonstrates the non-negative power constrain of the transmit power on each subchannel
- $SNIR_{n,l} \ge SNIR_{thr}$, which sets the minimum SNIR threshold for acceptable QoS.
- $N_{l,t} \le N_{thr}, 1 \le l \le L, 1 \le t \le T$, where $N_{l,t}$ is the number of users, grouped in the l^{thr} subcarrier over time slot t, and N_{thr} is its upper threshold, in the case of NOMA transmission [51].

B. REPRESENTATIVE RECENT NON-ML APPROACHES

In this section, we summarize significant up-to-date approaches, which tackle the RRM multi-objective problem and do not make use of ML techniques (defined as "non-ML" throughout the rest of the manuscript). The relevant literature in this sub-section is representative with respect to various network metrics, such as throughput, QoS, interference mitigation.

In [52], a resource allocation scheme is proposed, where target SNIR values are accompanied by the minimization of power consumption. In the same context, in [53], the available spectrum is shared between macro and micro cells to maximize the number of users and achieve the SNIR requirements of each micro or macro cell user. In [54], a different approach is considered, where the distance-based resource allocation scheme is replaced by a model, based on priority classes of the mobile devices in mobile type communications (MTC) networks. This approach, apart from SNIR, considers latency, total induced delay and pending number of MTC devices, as well, for priority classes construction.

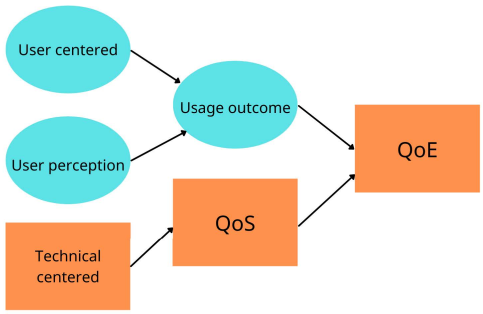

FIGURE 3. Relationship between QoS and QoE [54].

A key aspect in resource management policies in 5G networks is the harmonization with both QoS and QoE requirements. While QoS defines the user's satisfaction in a strict technical way, QoE reflects the overall user's happiness or frustration. The relationship between QoS and QoE is presented in Fig. 3. According to [55], there are two main (and one upcoming) ways to achieve the optimal joint satisfaction of QoS and QoE. The first one refers to the network's architecture and is the use of self-organized networks (SONs). The other one refers to the efficient tradeoff between packet loss, latency, traffic data (objective parameters) and mean opinion score (MOS), that should always exist. Last but not least, the integration of ML techniques in RRM, specifically NNs, which use data-driven (CSI-driven) techniques, in order to solve the optimization problem, can contribute in the direction of joint QoS and QoE requirements' satisfaction. These techniques will be deeply analyzed in the upcoming sections III and IV.

In the existing literature, the significance of both QoS and QoE requirements' satisfaction is highlighted. For example, the authors in [56] consider the resource allocation problem in M2M 5G 3GPP cellular systems. An optimal radio resource allocation method in LTE and beyond cellular networks is developed, based on adaptive selection of channel bandwidth, depending on the QoS requirements and priority traffic aggregation. Furthermore, a novel simulator is proposed, focusing on the joint impact of M2M and human-to-human (H2H) traffic in 5G networks. In order to ensure the satisfaction of QoS requirements, the proposed simulator automates RRM algorithms for both the M2M and H2H traffic. The simulations and results indicate that the proposed framework improves the radio resource management policies' application by 13%, concerning the LTE frame formation process.

Wang *et al.* [57] use QoE utility function for spectrum and power allocation in macro and pico–cell HetNets. For the subcarrier allocation method, they construct a weighted bipartite graph and revise Kuhn-Munkres algorithm to obtain perfect matching. For power allocation, they use the first-order derivative of the network utility function, achieving the nearly-optimal levels of power minimization. However, increasing the cell size results in QoE deterioration. In the same framework of using QoE utility function, the authors in [58] consider the joint subcarrier, assignment and power allocation problem. The proposed approach is based on the decomposition of the general problem into two sub-problems: the BS selection and subcarrier allocation sub-problem and the power allocation sub-problem. A genetic algorithm for the first problem and an artificial bee colony (ABC) algorithm for the second one are proposed. The simulation results indicate that the proposed power allocation scheme reaches optimal solution levels quickly, while MOS increases for increasing number of active UEs or available subcarriers.

In 5G HetNets, interference can have a critical impact on the selection of the appropriate RRM strategy. There are three types of interference. The first one is cross-tier interference, which occurs between users in different tiers, such as between macrocells and fempto-cells (FCs). On the other hand, co-tier interference is experienced by users within the same network tier [59]. Finally, inter-cell interference occurs mainly at the cell edges, where a user can receive signals from multiple BSs/RNs. The authors in [60] consider a 3-tier HetNet and propose a joint interference and resource allocation strategy. The examined use cases enhance D2D communications in macro and small cells topology. The joint sub-band and resource block (RB) allocation problem is solved, with respect to the QoS levels and D2D interference minimization. The proposed scheme alleviates significantly co-tier and cross-tier interference, compared to traditional techniques. On the other hand, the proposed algorithm introduces delays that could cause difficulties in the deployment of the scheme in real-world scenarios. In the same context, authors in [61] examine the influence of inter-cell interference in the design of effective RRM strategies. More specifically, they formulated an EE maximization RRM problem for a downlink OFDMA HetNet, and solved it via a two-step generic algorithm. The first step concerned subcarrier allocation under SE requirements, while the latter power management. Simulation results indicated that a trade-off between EE and total achieved throughput should exist, proposing small cell deployment as a way to simultaneously improve both factors.

Xu *et al.* propose in [62] a resource allocation scheme to maximize the system throughput, by considering cross-tier and co-tier interference for macrocell users, as well as the transmission power in HetNets. The proposed scheme uses a nonlinear programming formula, solved by distributed Lagrange dual methods. This method results in interference limitation for the users spread in the topology. However, the adopted approach involves many iterations, thus leading to increased overall delays.

In [63], a joint RRM problem is investigated and solved sequentially in an mmWave environment. The first one is related to beam selection (beamforming), while the second one to power allocation. These problems are formulated into mixed integer nonlinear programming (MINLP) problems. The authors solve the first problem using cooperative games theory. In this way, optimal beam allocation is achieved and served as input to the second problem, where the power allocation scheme is determined, employing Lagrange duality and an iterative water-filling algorithm. According to the presented results, there are significant throughput improvements, compared to classic RRM schemes. On the other hand, computational complexity is extremely increased, reaching almost prohibitive levels.

In [64], a similar joint routing and resource allocation problem is investigated, considering multi-tier analysis approach for mmWave systems. Resource allocation concerns the physical layer, while path selection concerns the network layer. A stochastic algorithm is used for RRM and a linear programming one for the path selection. The EE and the overall system throughput are significantly improved, compared to state-of-the-art algorithms. However, a lot of delay factors are inserted, due to the adopted cross-layer approach. Therefore, this scheme might be inappropriate, when dealing with URLLC demands in emergency situations.

Another significant metric that originates from throughput is SE, which is the "clear" information that can be transmitted over a specific spectrum area in a wireless environment. In this context, the authors in [65] propose a resource allocation system, based on SE requirements. They make use of a hybrid-clustering game algorithm, that mitigates co-tier and cross-tier interferences. The clustering problem is solved using graph theory, and more specifically a maximum K-cut algorithm in the interference graph of the topology. Then, inside each cluster, resources are allocated to users, implementing an auction game mechanism algorithm. According to the presented results, there are significant improvements, compared to state-of-the art approaches, in terms of SE and throughput. However, we should mention that, by the above scheme, both macro and micro-cell users are treated as one entity. In this case, the QoS and QoE metrics are not taken into consideration.

In ultra-dense modern era networks, power consumption becomes a key issue. Thus, the metric of EE is used to measure the power consumption in the topology [66]. In this context, a complex scheme is proposed in [67], that jointly maximizes EE and SE. There are three different components in the proposed scheme. The first one is a system to balance the load between the BS of service and other BSs in the topology, along with handover management. The second one aims to manage inter and intra-cell interference and frequency reuse. Finally, the third one applies a proportional fairness (PF) allocation policy to guarantee fairness among users. A binary search algorithm implements the resource allocation, maximizing EE and SE. Therefore, this approach is beneficiary for commercial use cases, due to the fast decision-making mechanism, leading to optimal solutions. However, the fully centralized nature of the algorithm might increase overhead, due to the increased round-trip time.

Another key issue in future networks is the limitation of usable resources to tackle the spectrum scarcity problem. Dynamic spectrum sharing is proposed as a novel method for the cooperation between 4G-LTE and 5G technologies, as different spectrum resources can be allocated, based on users demands, establishing improved SE levels and spectrum utilization. The authors in [68] proposed a dual bargaining game model to solve the spectrum sharing problem guarantee effective real-time collaboration between LTE and 5G systems. Results indicated that this scheme improves total throughput and service failure by 5-10% compared to traditional approaches.

Furthermore, the increased number of traffic load from mobile devices, which causes the densification of wireless networks, empowered the deployment of revolutionary centralized alternatives of the classical cellular architectures, such as Cloud RAN (CRAN) and O-RAN. In CRAN architectures the baseband processing unit (BBU) is moved from the BSs onto a centralized cloud/edge BBU pool, while O-RAN indents to provide open air interfaces and separate user and control plane functions. The authors in [69] proposed a two-stage optimization algorithm for the joint secondary user selection, spectrum allocation and time scheduling problem of downlink transmission in CRAN. Results indicated that improved data rates, time scheduling and prioritization for big data transmissions can be achieved using the above scheme. Concerning O-RAN, the authors in [70] implemented a mixed-integer linear algorithm to solve the joint distributed unit and subcarrier allocation problem, with respect to energy and latency minimization for delay-sensitive communications. Results indicate that the proposed approach consumes less energy under a larger network size, compared to a disjoined scheme.

C. LIMITATIONS OF NON-ML APPROACHES

In the previous sub-section, significant non-ML approaches, concerning RRM in 5G and B5G networks, are presented, where various sub-optimal solutions are proposed, due to the multiparameter nature of the problem. However, focusing on the outcomes and results of those research efforts, several limitations can be witnessed. In most cases of LTE and early 5G networks [56], [58], [59], [64], the enactment of the RRM policy was based on perfect knowledge of specific parameters, such as the instantaneous CSI and QoS requirements of the active users. Thus, the optimal allocation problem, described in the above paragraphs, is solved through optimization procedures. However, it is also apparent from the problem formulation that, in practical wireless orientations, multiple difficulties may arise, thus making resource allocation a multidimensional problem. More specifically:

- Most of the non-ML techniques provide solutions which are not universal. Optimal solutions are highly correlated to the current circumstances in each network's topology, user demands and qualifications. Thus, RRM, in general, is a problem characterized by non-conventionality [71].
- The provided solutions may not be obtainable in real time. HetNets and IoT networks have high levels of time variability. An optimal solution in a time slot or interval is not by default optimal for the next time unit [63], [64].
- The wireless channel in 5G and B5G networks is defined by an extremely high propagation scheme, with users characterized by random or partially unknown mobility patterns. In these scenarios, the mathematical formulation of the problem is arduous and, in general, not easily defined [67].

According to these considerations, more efficient RRM solutions should be implemented in both computational and performance perspective. In this framework, ML-based resource allocation algorithms are proposed in the literature, as an efficient way to deal with the abovementioned limitations. In the following paragraphs, after introducing the different types of ML, we present the state of research in the field and draw guidelines and considerations for future work.

III. ML ALGORITHMS IN 5G/B5G SYSTEMS FOR RRM OPTIMIZATION

A promising direction to tackle the challenges we highlighted in the previous sections is the deployment of ML [72], [73] in order to formulate a data-driven framework in wireless communications' RRM. AI/ML technologies are and will be used extensively in the 5G/B5G communications era, both in the CN and the RAN part of the 5G (6G) environment. In this direction, network slicing and traffic management, that enable improved network performance and reliability, are two representative problem cases of AI-assisted solutions [23].

However, the reported research in the field has mainly focused on the CN, in order to deal with the routing problem or to propose efficient network slicing implementations. In general, less research efforts are reported on traffic control or RAN. Moreover, for traffic control, until now the reported research has only focused on the network layer, with only a few research reports on the application of AI technologies to the physical, application or semantic layer.

In the following subparagraphs, the related research concerning the use of AI/ML in RRM is presented, classified in terms of type of learning and architecture (centralized vs distributed). The performance of the used models is also discussed, and conclusions are drawn upon them.

Finally, in order to present and discuss the existing literature concerning the use of ML in resource allocation in 5G and B5G networks, we first introduce in sub-section III.A the classification of ML algorithms, in terms of the type of data they process (labeled or unlabeled), as well as in terms of the corresponding mechanisms (see also Fig. 4).

A. TYPES OF MACHINE LEARNING

Supervised learning is based on a dataset with values accompanied by their respective labels. These labels can be produced either by humans or automatically by computation [23]. A common practice to deal with the dataset is to split it in a training and a test set, where the first one is used for model training. In other words, a mapping between the inputs and the labels is being produced. The most indicative use cases of supervised learning are classification or regression problems. The latter term refers to the prediction of a target numerical value, given a set of features/attributes, also called predictors, through an estimation function. In linear regression the estimation function is linear, while in logistic regression it is a common sigmoid. Classification refers to the prediction of a class label, by using classified example data as input. The basic difference, compared to regression techniques, is that the model displays the probability that a certain value belongs to a given class [73]. The system is trained by multiple examples of a class, along with their labels, in order to learn how to classify new instances. The ML techniques/algorithms, that are mostly used in RRM-related problems, are briefly presented below and will be reported again in section IV, where the corresponding literature is analyzed in detail.

A *k*-NN algorithm classifies instances by comparing its k nearest neighbor's labels. Then, the item is classified to the most common of them [74], [75]. On the other hand, Support Vector Machines (SVMs) are used for both classification and regression. Data are plotted as a point in an n-dimensional space, where n is the number of features of the dataset, and classified by finding the hyper-plan, which differentiates the problem's classes in an optimal way [76]. Decision trees can be used, either for regression or classification purposes. However, traditional decision trees approaches record high variance levels, due to their sensitivity to training data. Aiming to prevent this problem, alternative approaches are implemented. For instance, bagging trees classifiers use bootstrap simulations to generate reliable results [77]. A major category of supervised learning techniques is the artificial neural networks (ANNs). These learning algorithms are inspired by brain, in order to simulate, predict or store information. Their basic building units are neurons and the connections between them, which formulate the model. ANNs are used both in regression and classification problems.

Furthermore, overfitting/underfitting should be checked at each time a model is formed, in order to prevent inserting errors, making it unable to depict properly all the attributes of the tested dataset. Underfitting occurs when the model is not able to obtain a low error on the training set [78]. This means that the model cannot describe all the characteristics in the dataset. On the other hand, overfitting takes place, when a significant difference between the errors in training and implementation (training set vis a vis test set) is detected [79]. This means that the model describes more characteristics, than the actual ones.

Unsupervised Learning differs from supervised learning (see Fig. 4b), as the model itself tries to identify the common characteristics of the dataset [23], [79]. Moreover, labels are not included in the dataset, as the system tries to find them without external help. However, the concept of training and test data remains the same. We only insert, as input in an unsupervised model, the number of clusters or characteristics to be mined. By the term cluster, we refer to the number of distinctive groups, in which the dataset is classified.

Finally, **Reinforcement Learning** uses a learning entity, often called agent. Agents act as representatives of the system, for its collaboration with the environment. The information feedback that the agent returns to the model is called rewards (positive case) or penalty (negative case). In that way, the agent creates a policy to set up its own learning scheme and decide which actions to choose in a certain situation. The aim of the RL task is to maximize the reward over time [78].

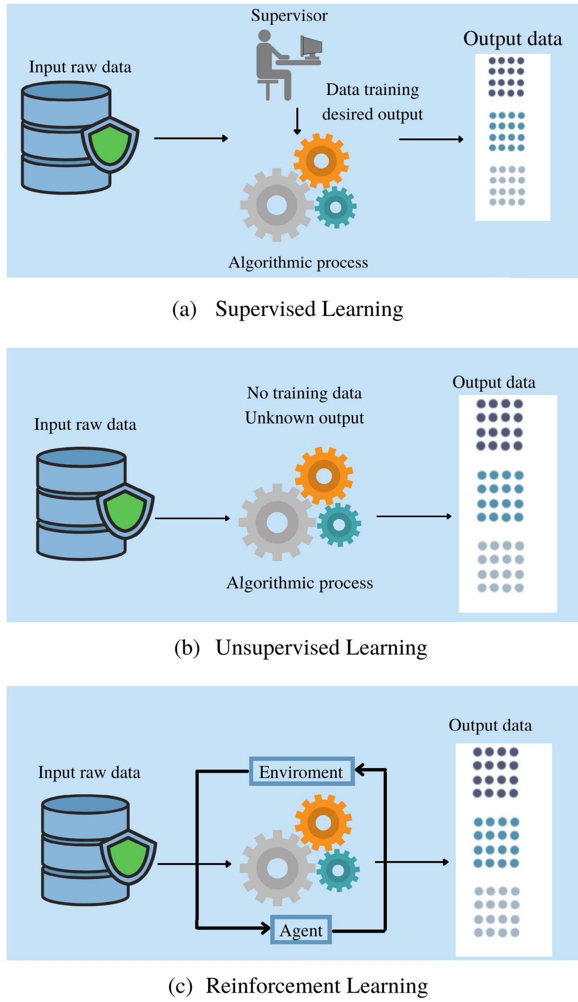

FIGURE 4. Types of learning: (a) Supervised learning, (b) Unsupervised learning, (c) Reinforcement learning.

B. SUPERVISED LEARNING

The authors in [80] consider a SON topology. A 5G network simulator is proposed, along with a pathloss model, using metrics, such as SNIR and throughput (LTE KPIs) in order to deal with the problem of dynamic frequency and bandwidth allocation in these topologies. The system is tested in several frequencies and bandwidths. In order to set the RRM policy and predict the KPIs, several ML methods, such as bagging trees, boosted trees, SVMs and linear regressors are evaluated. Bagging tree prediction witnesses the best overall performance. The main feature of this method is that it uses bootstrap sampling in deep decision trees, in order to reduce the variance of the model and classify data correctly to predict the network's KPIs. According to the derived results, the decision tree learning-based method reaches 95% of optimal network's performance. Finally, the authors highlight the necessity for a joint consideration of networks' KPIs and ML performance metrics.

Working also on KPIs prediction, the authors in [81] design a predictive model for the overall users' demand. Then, they use an ML-based supervised classifier to allocate the network resources dynamically (Network Resource Allocator). The employed metrics are bandwidth, latency, jitter times, QoS and QoE. The decision process for data traffic and allocated subcarriers is defined by QoS and QoE. The learning procedure is based on previously gathered experience from offline measurements. Thus, the proposed Network Resource Allocator empowers an automated flexible and elastic network. The models are employed in the network's controller in order to change the network topology for better traffic management by removing the unused parts of the network to release its unused resources (i.e., subcarriers, unused links, etc.).

In m-MIMO systems, hundreds of antennas are used for detection, resources' allocation and channel estimation (via channel coefficient matrix). In [82], an SVM scheme is proposed for the estimation of the Gaussian channel's noise level and pathloss prediction in urban outdoor environments. The general form of the problem has t transmitting MIMO antennas and r receiving ones. The model predicts the channel noise statistics, according to which the allocation and multi-tier QoS scheme will act for each independent user or users' category. Three kernel techniques are investigated (Polynomial, Gaussian and Laplacian) and compared to the Okumura-Hatta pathloss model and an ML-based ANN one. Laplacian SVM witnesses the best performance, in respect to both pathloss prediction and computational complexity. The overall satisfactory performance of the SVM approach is due to the use of multi-dimensional representations in feature extraction, leading, thus, to reduced training time and increased capacity. ANNs' performance is similar to SVMs' approach, needing though longer training times, as multiple initializations are requested.

Considering DL approaches, Liu propose in [83] an ANN algorithm for channel learning, to mine undiscovered channel information data from a 5G network. They use location features and CSI and they produce channel samples from 5G simulators, that are latter used as training data for the model. The channel ANN estimation algorithm calculates unseen aspects of the channel approximation and resource allocation scheme. The prediction accuracy improves, compared to traditional k-NN classifiers. It remains, though, limited to a level of 75%, but could be further increased by approximately 3%, if geographical information is used in the dataset.

Zhang *et al.* [84] build a deep NN (DNN)-based framework for user, subchannel and power control in NOMA mmWave networks. The solution of the user association problem is given by the Lagrange dual decomposition. The subchannel and PRB allocation is given by a semi-supervised learning algorithm, while the power allocation is given by a DNN model. The use of the described joint ML-based component (for user, subcarrier and power control) delimits the entire decision-making policy in terms of RRM. According to the presented results, the EE of the system is significantly improved, while the resource allocation reaches optimal levels (98% accuracy).

Guerra-Gómez *et al.* [85] propose a dynamic resource management scheme, based on the prediction of the total system's capacity. They use three different ML algorithms: SVM, DNN, and LSTM. According to the presented results, the scheme can perfectly reduce the underutilized resources; however, QoS levels are not optimized. Therefore, the authors propose two novel strategies. The first one considers data pre-filtering and results in an additional 2% minimization of unallocated resources. The latter one considers error shifting and leads to an additional 3% reduction in unallocated resources. However, the achieved QoS levels form a barrier in this approach.

The authors in [86] consider the problem of optimal and automatic BS selection in LTE and 5G environments. They propose two ML-based classification solutions to satisfy QoS requirements; the first one uses SVMs and the second one Random Forest. Both approaches are compared to a non-ML BS selection approach. The results indicate that the ML-based BS selections can improve throughput and decrease outage probability and delay. Specifically for a 50-user topology, ML approaches achieve 23.21% higher throughput levels, 70% lower packet loss ratio and 48% lower delays compared with a non-ML approach.

In the same framework, Butt *et al.* [87] investigate the UE positioning problem in 5G networks. The authors compare a decision tree classifier with two DNN solutions. The first one uses training data from the service cell and overperforms in terms of accuracy, while the second one uses transformed data from the cell and its neighboring ones. In general, the DNN solutions witness an overall near-optimal performance, in terms of accurate positioning of UEs. In fact, the 2-hidden layer DNN witnessed a positioning error in the range of 1-1.5 m, after appropriate feature selection.

C. UNSUPERVISED LEARNING

Song *et al.* [88] produce a realistic 5G V2V networks' simulator, with the presence of RNs. A k-Means clustering algorithm is responsible for implementing BS or RN selection, user allocation and serving policy. User positioning and RN distribution in the topology are performed via ML, in a way that the serving device, BS or RN, is optimally selected. However, the model calculates every 2D distance from the observation point (in that case UE) to the borders of each cluster and not to the cluster center. Thus, the overall communication environment parameters are not taken into consideration. Moreover, since the proposed k-NN algorithm is a generic unsupervised ML method for clustering, its performance can be affected, if UEs have a complex spatial distribution or clustering is performed in different topologies. However, the authors intend to further improve and configure the algorithm, to define a more efficient selection strategy.

The authors in [89] propose a data-based resource allocation scheme, where an ML technique of affinity propagation is used. In general, this approach uses graph theory to perform clustering. The basic advantage of the proposed algorithm is that it does not require the number of the clusters as input. In this way, knowledge and behavior extraction can be made even under complex scenarios. The authors conclude that the data-driven nature of the RRM policy improvs both system's EE and throughput, although, in some cases, the QoS levels are not the desired ones.

Wang *et al.* propose in [90] an asynchronous resource allocation scheme, based on aggregation graph NNs (Agg-GNN). In this approach, every BS or RN aggregates information from its active neighbors with a certain delay. Thus, both the underlying network structure and the system's asynchrony are incorporated. According to the presented results, this approach outperforms heuristic ones, in terms of the total system's capacity. The presented simulations, though, used only a small number of active UEs in the topology. Probably, in more complex environments, GNNs' training time might increase, and, thus, performance might deteriorate.

In [91], the authors propose an integrated scheme for resource management in NOMA environments. The first stage of the algorithm refers to the users' grouping and subcarrier allocation, while the latter one to the power control. UEs are grouped via the *k*-Means method, while subcarrier allocation and cluster definition are calculated using the F-test method [92]. Power assignment is performed for the allocated subcarriers, by formulating a convex optimization problem. The presented results indicate that the proposed approach reduces electromagnetic exposure and increases the total served users. Although in this approach single antenna configurations are used, both in the BSs and the UEs, the authors are aiming to extend their work to MIMO systems.

D. REINFORCEMENT LEARNING

Alnwaimi *et al.* used RL in [93] to increase spectrum accessibility in FCs. The proposed scheme identifies the available spectrum opportunities; then, it selects subchannels, so that they operate avoiding intra/inter-tier interference and meet certain QoS requirements. A key aspect of this approach is that the considered method reaches optimal levels, in terms of sub-carrier allocation, even in tiny cell topologies. The basic contribution of this approach is the reduced convergence time and the fast decision making procedure. However, these come at the cost of reduced accuracy which is now limited to 75%.

In [94], an RL-based algorithm chooses the frequency channel and determines whether to change its location in the presence of jamming and strong interference. A Q-learning algorithm determines the above decision, while a deep CNN accelerates the channel feature extraction. The scheme operates extremely well for huge channel numbers, in terms of interference mitigation, and increases SNR levels compared to a simple Q-learning system (without CNN).

The authors in [95] propose a deep RL framework for power control in 5G HetNets. The problem is formulated aiming to minimize the difference between the mobile users' allocated and requested throughput, by adjusting the transmitted power of the macro-BS or RN. According to the presented results, the proposed approach reaches optimal levels of users' satisfaction, based on achieved throughput compared to traditional water-filling [96] and weighted minimum mean squared error (WMMSE) approaches [97]. However, as expected, the difference between user demands and allocated throughput is increased, as the user requirements do so.

The authors in [98] propose a distributed multi-agent deep RL (MARL) framework for joint user and power allocation, in a dense wireless network. The data are generated by real measurements and backhaul delays. The results, via simulations in dense wireless networks, indicate that the scheme achieves a tradeoff between sum-rate and 5th percentile rate, similar to centralized scheduling algorithms. The authors intend to verify the performance of the RL scheme in real-world scenarios in the future.

The authors in [32] use QoS as the basic metric in an ML-based resource allocation scheme. An RL (Q-learning) algorithm is used for the radio access technology (RAT), while the actual RRM is developed, employing the monte-carlo tree search (MCTS)-based Q-learning algorithm. The authors prove that optimization is achieved after a reasonable number of searches and that it outperforms other scheduling methods, with respect to the system throughput and resource utilization. However, the computational complexity is increased, due to the exhaustive use of the MCTS method. This could be a disadvantage in real case scenarios.

Moreover, RL methods are utilized [33] in order to minimize the total transmission power in HetNets, while jointly satisfying the bit rate requirements of different UEs. Every UE can be connected to one of the available BSs or to another UE, which acts as an RN. The authors use Q-learning in the decision-making procedure. The proposed algorithm reaches optimal levels, in terms of the resource allocation. In addition, the decentralized nature of the algorithm, constitutes a very promising approach with future extensions, as it uses specific UEs as BS/RNs.

RL methods have been also used in 5G satellite communications to efficiently perform RRM related tasks. More specifically, the authors in [99] propose an intelligent RL wireless channel allocation algorithm for 5G m-MIMO High Amplitude Platform Station (HAPS) networks, based on Q-learning and back-propagation NNs. The entire network is trained using the Q-learning model, while CSI information is collected in the platform, through real-time agent interaction with the environment, and thus, updating the Q-algorithm using a back-propagation NN. Results indicated that, even if the number of agents is very high, the channel allocation accuracy levels remain high (over 75%).

E. DISTRIBUTED TECHNOLOGIES AND ML

As already pointed out in the previous sub-sections, an important bottleneck in 5G networks is data overload, in conjunction with the limited storage and computational power of UEs and BSs. A recently proposed solution is to use distributed structures for processing reasons (Fig. 5). In wireless

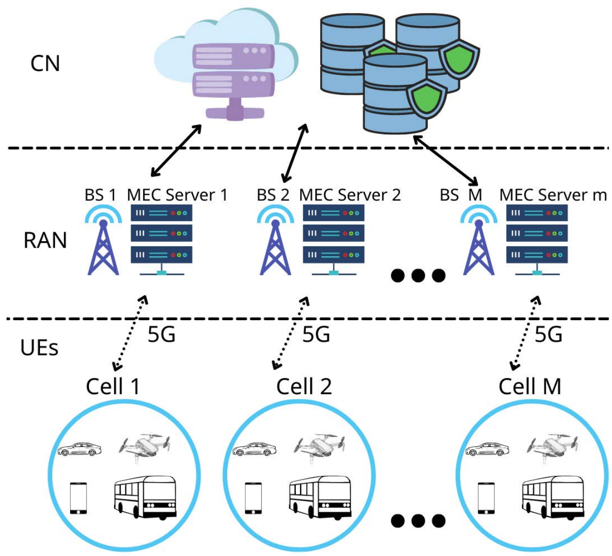

FIGURE 5. MEC implementation.

networks, this is mostly achieved via MEC architectures, where cloud, edge and mobile processing cooperate [9]. MEC and ML are inextricably related concepts. MEC, being a distributed approach, uses ML tools in heterogenous topologies (such as 5G and 6G networks) to obtain CSI till the network's edges, in order to define the resource allocation policy in each case. The goal of MEC is to minimize the computation time, by allocating the traffic to different processing units.

In that case, as described in [100], the processing time overperforms the corresponding processing time without MEC. If user n sends a computation task j to a MEC device m, then the total MEC latency is given by the transmission time of task j from user n to the processing unit m, plus the user delay to process the task, plus the execution time in the MEC device [101].

Focusing on MEC technologies in RRM, the authors in [101] present the state-of-the-art on the employment of MEC networks, focusing on architecture, cashing, computation and use of ML-based schemes. In general, caching refers to the temporary storage of content (CSI in RRM-related tasks) in centralized or decentralized databases, for future access. The reasoning behind those storages is that an instance (i.e., a D2D communication in RRM), that has occurred once, is very likely to occur again in the future. In MEC systems, these techniques are commonly used for decision making and allocation of available resources. For example, the authors in [102] reach a 10 – 11% lower latency and improvements in QoE, compared to non-caching schemes. The authors in [103] propose an efficient content caching policy for edge using dynamic ML predictions. The proposed Long-Short-term Memory approach provided 30% higher caching ratio, than conventional approaches.

MEC and ML are combined in complex optimization problems, as well. In this context, resource allocation, beamforming and caching issues can be jointly encountered. Related works in this field use DL models, such as ANNs, for accurate computations. Such efforts are described in [104] and [105], considering decentralized hybrid beamforming in 5G next generation node BSs (gNodeBs). The proposed novel techniques (CNN frameworks in both [104] and [105]) outperformed state-of-the-art optimization-based and greedy-based algorithms, both in terms of SE and computational complexity.

A synergy of MEC and ML is also achieved through federated learning (FL). Counter to centralized ML methods, where local data (from UEs in 5G/B5G networks) are uploaded to a centralized server, and also counter to classical distributed approaches, where data are uniformly distributed among the edge devices, FL schemes use local data to train a global model, through multiple training iterations across interconnected edge devices (UEs), in order to achieve the desired global accuracy. Then, local updates, generated by each interconnected device, are aggregated to a cloud or a MEC server (in BSs) (Fig. 6). The required accuracy is achieved by multiple communication rounds between the server and the edge devices, which train the model with their local datasets. Thus, the total training time is a key aspect in FL model design [106], [107]. The main reason, that renders FL implementation an efficient method in distributed computation problems, is the privacy and security that is achieved through the local training of the model and the secure aggregation to the server entities. However, in RRM-related tasks, active UEs or edge devices have different processing power, antenna characteristics and mobility patterns, leading, thus, to heterogeneity in local datasets. More specifically, the data generated in each UE contain different labels and/or features and are not of the same volume. This is called non-independent and identical distribution (non-IID) in the generated data [106]. Therefore, the purpose of implementing FL schemes in RRM (i.e., resource allocation, latency minimization) is, also, to address the aforementioned heterogeneity and, in that way, improve the accuracy of the global model [108].

In this framework, the authors in [108] propose a UE scheduling method in an FL-assisted wireless network, based on the joint quality of channel and learning optimization. When wireless resources are limited, this method improves the overall training time, compared to traditional ones. However, the model's accuracy decreases in an environment with powerful resources, due to data overload.

To deal with the problem of training latency in different topologies of the network, the authors in [109] consider joint optimization for user selection, frequency and transmit power allocation, using the Majorize – Minimization algorithm and phase shifting, by employing semidefinite relaxation and Gaussian randomization, to reduce the training time of the FL wireless system.

Concerning distributed computation and MEC employment in 5G/B5G networks, the classical hierarchical structure of a cellular network is proposed to change in order to become

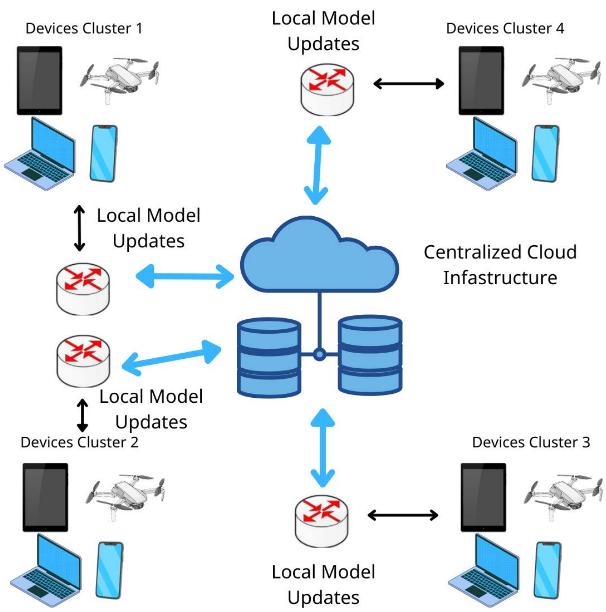

FIGURE 6. **FL in 5G/B5G networks.**

more flexible and decentralized. In this framework, O-RAN and CRAN architectures, analyzed in Section II, are about to efficiently satisfy the joint requirements of increased throughput levels with respect to QoS and QoE standards, and also to the concept of low-energy green networks. With respect to the aforementioned considerations, the authors in [110] proposed a deep Q-learning framework in CRAN to maximize EE subject to the constraints analyzed in Section II-A. As previously stated, the Q-learning method uses past learning experience to predict future effects and make reward/penalty decisions. However, sometimes action overestimation generates lower probability limits for the maximum Q-value. With the use of a double Q-learning model, the target Q-value generation leaded to bigger energy savings, whereas numerical evaluation indicated that the method reduces by 22% and also, improves EE at the same rate. Considering an O-RAN architecture, the authors in [111] propose an RL based RRM solution and deployed it in the ecosystem. The O-RAN Distributed Unit sends periodically reports to the O-RAN Interface and a dynamic per-flow resource allocation strategy is employed to set the modulation and coding scheme, according to KPI requirements.

F. SUMMARY–COMMENTS

Table 2 summarizes the usage of ML in 5G/B5G RRM problems, and groups accordingly the research papers presented in sub-sections A÷D.

As already stated in section III and verified by Table 2, Supervised Learning techniques are mainly used for prediction purposes. Indeed, various networks' KPIs (throughput, SNIR, pathloss) can be effectively predicted, in order to empower allocation strategies [80]–[82]. DL methods, due to their ability to mine deep data and label associations through multiple complex hidden layers (ANNs, DNNs, CNNs), are mainly used in user, subcarrier, power allocation and CSI prediction tasks [86], [87]. The multiparameter nature of the RRM problem and the complex channel feature associations render DL approaches as the most efficient way to deal with the total RRM problem [83]–[85].

On the other hand, Unsupervised Learning focuses, in general, on clustering: the corresponding models are efficient in user grouping, BS or RN selection and QoS levels formulation, concerning RRM tasks [88]–[92].

RL models -as DL ones do- are more efficient dealing with the NP-Hard problem of the overall resource allocation. In this framework, RL approaches, such as Q-learning, are proposed by researchers in joint user, subcarrier allocation and energy consumption minimization problems [93]–[99].

Finally, MEC and FL methods, which refer to the most recent evolution in the field, are proposed to face the challenging issue of training time minimization, latency minimization and computational resources optimization [102]–[111].

From the above analysis and Table 2, a categorization of the best performing ML algorithms for each RRM-related sub-problem is visible. As presented in Section II, the NP-hardness of the joint subcarrier allocation and power control with respect to QoS, QoE constraints has led recent research efforts to deploy more intelligent solutions, which have the ability to communicate with the cellular environment, and change their predictions and decisions (DL, RL, FL methods), based on the current conditions. However, the existence of big data in transmission systems and wireless networks necessitates the utilization of classical ML approaches, such as supervised ones, specifically in order to tackle problems where the knowledge of a KPI and/or CSI is vital for low latency responses and fast decision making (e.g. for coding and/or modulation scheme selection in each timeslot).

Despite the growing activity on ML usage in resource allocation, the existence of several limitations and open issues, that will be analyzed in the next section, motivate further research.

IV. SIMULATIONS AND COMPARISON

In this section, the performance of various ML algorithms for KPI prediction is presented. The investigated ML algorithms have been selected based on two criteria. The first criterion is their ability to satisfactorily solve the KPI prediction problem. This means that we have selected algorithms with performance scores over 75%. The second criterion is the usage of these algorithms in RRM-related KPI prediction task in 5G/B5G networks, according to the presented literature in the previous sections (i.e. [79]–[81], [89]–[91]). More specifically, using the Lumos-5G dataset [112], the problem of throughput prediction is investigated (Lumos5G features are summarized in Table 3). The dataset contains 68,118 observations of 19 features, concerning UEs' location and mobility parameters, such as longitude, latitude, UE speed and direction, UE-BS distance and corresponding angles, as well as network related ones, such as network status (connected or not), CSI parameters (Received Signal Strength Indicator – RSSI, Reference Signal Received Power – RSRP, Reference Signal Received Quality – RSRQ, SNIR), and signal strength, derived by real-world experiments and statistical analysis. The measured downlink throughput acts as the response variable. Throughput prediction is formulated, either as a classification or as a regression problem. On the one hand, classification refers to the prediction of the received throughput level by each active UE, given the dataset features. The effective solution of this problem can be valuable in a variety of RRM-related tasks, such as modulation levels definition.

On the other hand, regression refers to the prediction of the actual expected value of the metric (throughput in our case). The information gathered by the regression task can be valuable in RRM decision tasks, such as subcarrier and/or power allocation, via the prediction of the values for next timeslots.

Considering throughput prediction as a classification problem, two different approaches are considered in our analysis. The first one concerns three preselected throughput levels (3 classes):

- *Level 0 – low throughput:* from 0 to 300 Mbps,
- *Level 1 – medium throughput:* from 300 to 500 Mbps, and
- *Level 2 – high throughput:* above 500 Mbps.

However, due to the small amount of data in the second class of the previous approach, we consider also an alternate approach, where two preselected throughput levels exist (2 classes):

- *Level 0 – low throughput:* from 0 to 300 Mbps,
- *Level 1 – medium throughput:* above 300 Mbps.

The above-presented level limit values -in both 2-class and 3-class approaches- have been generated after performing extensive statistical analysis to the used dataset, concerning the goal of including satisfactory samples in each investigated class. Thus, we examine four distinct ML-based algorithms:

- *FFNN:* A Feedforward NN with 100 hidden layers and rectified sigmoid activation function (ReLU) and optimized hyperparameters,
- *k-NN:* A *k*-NN-based classifier using 2 neighbors and Chebyshev distance criterion,
- *SVMs:* Two SVM models, one using polynomial and another using Gaussian kernel and
- *DNN:* A Deep NN with a feature input layer -using the 19 features of the dataset- and z-score normalization, a fully connected layer with 19 × 50 weight matrix and a 50-element vector output, a 50-channel batch-normalization layer, a ReLU layer with a 50-element vector output, a second fully connected layer with 3 or 2 (3-class and 2-class problem respectively) neurons and 50 × 3 (3-class problem) or 50 × 2 (2-class problem) weight matrix and a 3-element/2-element vector output and, finally, a soft-maximization layer with a 3-element/2-element vector output. The overall DNN's structure for the 3-class problem is shown in Fig. 7. DNN's structure for the 2-class problem is similar and differs only in the size of the two last layers (fully connected layer 2, soft-max layer).

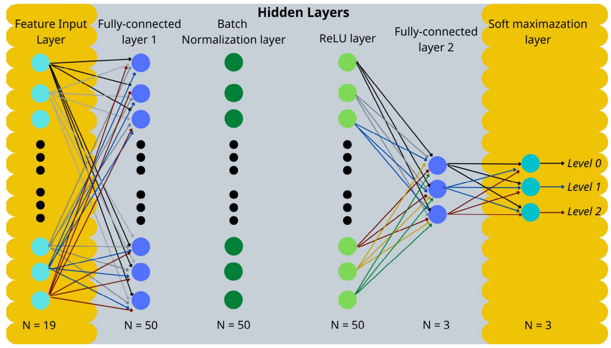

FIGURE 7. DNN's architecture.

TABLE 3. Lumos5G features.

Feature	Description
timestamp	day, time logs
longitude, latitude	geographical coordinates of each UE
detected Activity	walking, still, driving
moving speed	UE's moving speed using Android API
compass direction	horizontal direction of travel of the UE
radio type	5G or 4G
cell ID	number of the BS that each UE is connected to
signal strength KPIs	RSSI, RSRP, RSRQ, SNIR
UE to BS distance	distance between each UE to the server BS
positional angle	angle between each UE and the corresponding BS
mobility angle	distance between each UE's trajectory route and the corresponding BS
throughput	downlink throughput using iPerf 3.7

In both of the abovementioned approaches, an 80%-20% training-test set split has been used, as well as a 10-fold cross validation procedure. The performance of the abovementioned classifiers is evaluated, using the accuracy and F1-score metrics. Accuracy is the percentage of the total number of the correct predictions divided by the total number of observations. In other words, accuracy is the sum of True Positive (TP) and True Negative (TN) predictions, divided by the number of the total predictions (TP + TN + False Positive (FP) + False Negative (FN)). Then, F1-score is given by the following formula:

$$F1 = 2 \cdot \frac{\frac{TP}{TP+FP} \cdot \frac{TP}{TP+FN}}{\frac{TP}{TP+FP} + \frac{TP}{TP+FN}} \tag{6}$$

Table 4 summarizes the performance of the above models in the classification task (with two or three classes), based on classification accuracy and F1-score. The *k*-NN-based approach overperforms all the other approaches, witnessing the best overall accuracy (0.87 and 0.90 with three and two classes, respectively). In general, supervised learning algorithms (such as *k*-NN) are the most appropriate ones in networks' KPIs prediction, as drawn from the existing

TABLE 2. Research work on ML techniques in 5G/B5G RRM.

Type of Learning	*RRM Problem*	*Proposed ML approaches*	*Related Work(s)*
Supervised Learning	KPIs prediction (demands, SNIR, throughput, capacity)	SVMs, decision trees, regressions	[80], [81]
Supervised Learning	pathloss prediction	SVMs	[82]
Supervised Learning and Deep Learning	user and subcarrier allocation, power control, CSI prediction	DNNs, CNNs, LSTM, SVMs, Random Forest	[83], [84], [85], [86], [87]
Unsupervised Learning	RN or BS selection	unsupervised k-NN, k-Means clustering variations	[88]
Unsupervised Learning	user grouping, clustering, handover management	k-NN, k-Means, Agg-GNN, f-test	[89], [90], [91], [92]
Reinforcement Learning	subcarrier allocation, power control, frequency selection	MDP, DRL, Water-Filling, WMMSE	[93]. [94], [95], [96], [97]
Reinforcement Learning	minimization of difference between requested and active KPIs (throughput, SNIR, CSI)	Deep MARL	[98]
Reinforcement Learning	energy consumption minimization and resource allocation	Q-Learning	[32], [32], [33], [99]
Distributed Learning and MEC	caching CSI information, beamforming	ANNs, DNNs, CNNs	[101], [102], [103]
Distributed Learning and MEC	subcarrier and power allocation	CNNs	[104], [105]
Federated Learning	scheduling and training time minimization	majorize, semidefinite relaxation and Gaussian randomization	[108], [109]
CRAN/O-RAN	Resource allocation, EE minimization, modulation and cosind scheme selection	CNNs, Q-learning	[110], [111]

literature, analyzed in subsection E of section III. However, concerning F1-score, DNN has the best performance (0.81) in the 3-class problem, while k-NN (0.90) in the 2-class model. As stated in previous paragraphs, DL algorithms, due to their multiple hidden layer architecture, witness unseen aspects of the dataset, and, thus, their performance is satisfactory in the classification task. In this case, the preselected classes are imbalanced. Therefore, F1 metric is more reliable, because it concerns both TP, TN and FP, FN, while accuracy takes into account only TP, TN. It is also visible from Table 4, that, using only two classes, both accuracy and F1-metrics are improved. Moreover, with respect to the training time of each ML model we observe that k-NN overperforms the other approaches, while the DNN approach reaches almost the same performance levels. Thus, these two ML methods are the most appropriate for the investigated problem in both performance and training time perspective. On the other hand, FFNN approach has significant delay in training time, even though the performance accuracy almost coincides to the best-performing algorithm's one.

TABLE 4. ML Classification algorithms comparison.

ML Algorithm	**3 classes**		**2 classes**		**Training time (s)**
	Acc.	*F1*	*Acc.*	*F1*	
FFNN	0.81	0.67	**0.88**	**0.88**	961.40
k-NN	**0.87**	0.77	**0.90**	**0.90**	**111.79**
SVMs	0.76	0.53	0.82	0.82	150.03
DNN	0.81	**0.81**	0.85	0.84	129.43

Figs. 8, 9 depict the comparison of selected state-of-the-art throughput classification approaches [113]–[115] while the previously presented evaluation analysis is included as well. For each of the [113]–[115] works, we pick the best performing ML algorithm, and so we do for our evaluation approach, as far as the 3-class throughput prediction problem is concerned (i.e., k-NN algorithm, see Table 4). As it is apparent, our evaluation approach is consistent with similar approaches in other recent works [113]–[115].

Considering throughput prediction as a regression problem, the following algorithms are examined:

- *Linear regression:* A multi-linear regression model, using all 19 dataset features except throughput, which is the response variable,
- *Binary Decision tree:* A Gaussian binary decision tree designed for regression purposes, using auto-optimized hyperparameters,
- *SVMs:* Two SVM models, one using polynomial and another using Gaussian kernel and
- *NN:* A Feed Forward neural network with 100 hidden layers, a feature input layer with the 22 features of the dataset and z-score normalization, a 50×50 fully connected layer, a 50-channel batch-normalization layer, a ReLU layer, a soft-maximization layer and a regression layer.
- *LSTM:* A LSTM neural network with a sequence input layer for the 22 features of the dataset, an LSTM layer with 125 hidden units, a fully connected layer and a regression layer.

Similarly to the investigation of the problem as a classification one, an 80%-20% training-test set split is used, as well as a 10-fold cross validation procedure. The performance of the abovementioned ML models is evaluated using the mean absolute error (MAE) and RMSE metrics. MAE is defined as the difference between the actual and the predicted values of

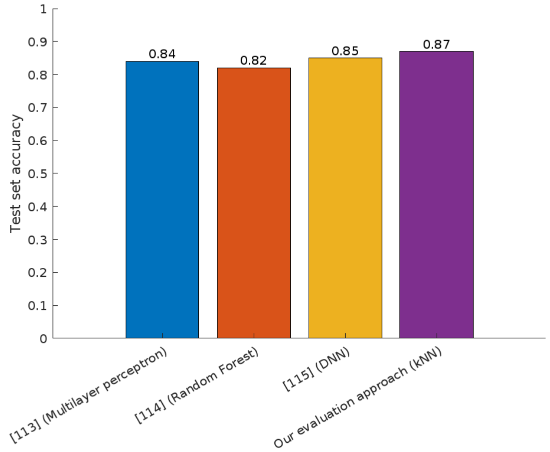

FIGURE 8. Classification models comparison: accuracy.

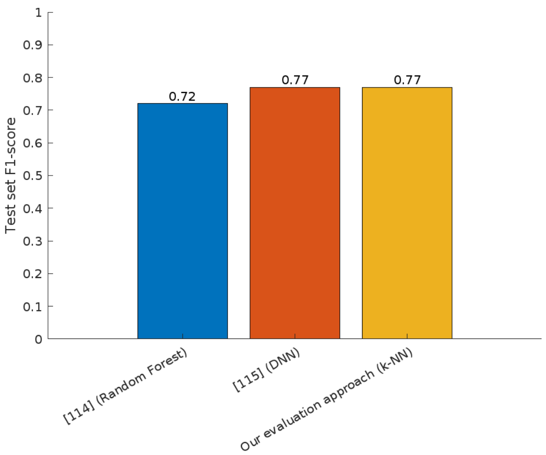

FIGURE 9. Classification models comparison: F1-score.

the response variable (throughput), while RMSE is defined as the square root of the squared difference between the actual and predicted values.

Table 5 and Figs. 10, 11 summarize the performance of the above models in the regression task, based on MAE and RMSE. The two best performing ML-based approaches are Binary Tree regressor and LSTM regressor, witnessing the best overall MAE and RMSE performance (162,257 and 150, 250 respectively). As in the previous case (classification problem), supervised and Deep learning algorithms are the most appropriate ones in networks' KPIs prediction as a regression problem. In fact, decision tree algorithms and linear regressors are designed for regression purposes. However, NN model's performance is also highlighted, as it is the second best in both metrics (237 and 328, respectively).

Fig. 12 depicts the comparison of the state-of-the-art throughput prediction approach in [113] with our previously presented evaluation analysis for the regression problem. We pick the best performing regression ML algorithm of [114], and so we do for our evaluation approach. (i.e., LSTM regressor, see Table 5). The comparison is

TABLE 5. ML Regression algorithms comparison.

ML Algorithm	MAE	RMSE	Training time (s)
Linear Regression	278	353	1.05
Binary Decision Tree	162	257	50.61
SVMs	278	354	28.84
NN	237	328	**6.89**
LSTM	**150**	**250**	276.89

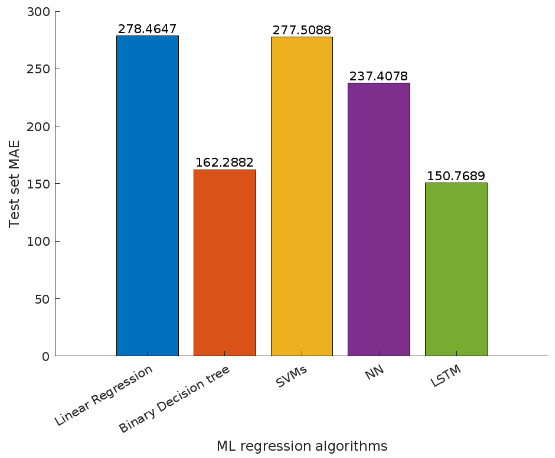

FIGURE 10. Regression models: MAE.

conducted using RMSE as metric. As it is apparent, our evaluation approach is consistent with the approaches in other recent works [114].

To conclude, we observe that, in general, both our approaches and other recent works on the KPI prediction problem for 5B/B5G networks propose Supervised or DL models as the most appropriate tools for this type of problem either as a classification or a regression one. On the one hand, supervised learning models (k-NN, SVMs, Random Forest) seem to have the best performance concerning training time. But on the other hand, DL (DNNs, LSTM) models overperform when it comes to performance metrics, such as accuracy and F1-score for classification purposes or RMSE, MAE for regression ones.

V. DISCUSSION AND OPEN ISSUES

As already stated, the allocation of the available network resources is a multi-objective problem, due to the diverse nature of users' requirements, hardware evolution and demand for continuous connectivity. Despite the research progress presented in section IV, some open questions and practical challenges persist, requiring even more effort in the field of ML-based RRM, to reach its full potential. The critical issues that should be taken into consideration are highlighted below and summarized in Table 6.

1) 5G and B5G networks utilize ML-based algorithms to phase the growing number of usage scenarios in access management. Therefore, ML performance metrics (such as RMSE for regression problems, accuracy for classification ones, etc.) should be examined

TABLE 6. Open issues and potential solutions concerning ML employment in RRM.

Open Issues	Potential Solutions – Suggestions for Future Work
networks' KPIs and ML KPIs joint evaluation [78], [86]	ML methods' evaluation in terms of network performance [79], [97]
5G datasets unavailability/poor quality [101], [116]	research work in dataset generators, real-world data availability [111], [113]
channel complexity [103]	DL approaches [113]
computational time and cost [81], [90], [96]	distributed DL, use of MEC and FL [82], [87]
energy consumption [38]	MEC, Green AI techniques [38]

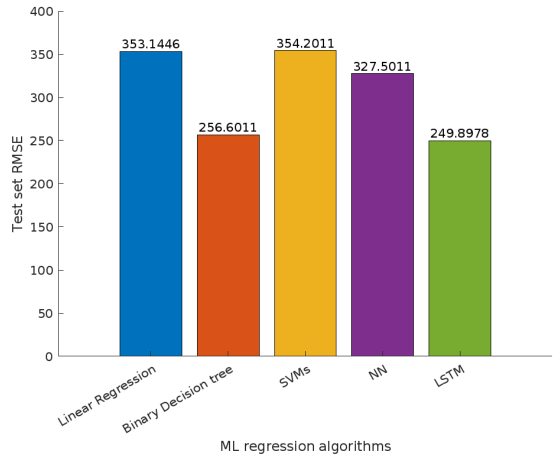

FIGURE 11. Regression models: RMSE.

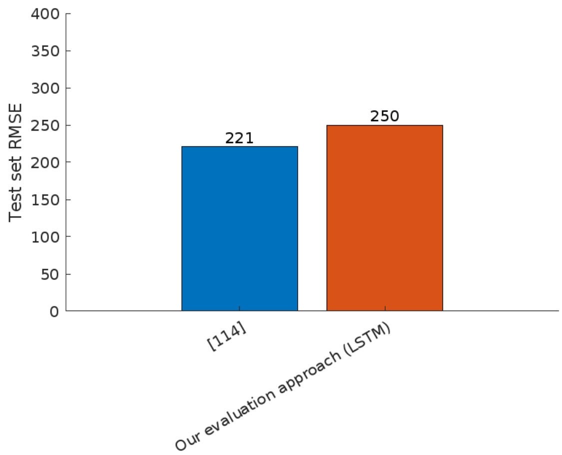

FIGURE 12. Regression models comparison: RMSE.

along with the network metrics (i.e., total network throughput, QoE, etc) [80], [88]. Some approaches (e.g. [79], [85]) focus only on the ML metrics performance increase, without evaluating also the networks' metrics.

2) Throughout this manuscript, we have presented the critical role that AI/ML plays in wireless networks and in IoT and heterogenous topologies, in general. However, researchers should not overlook some practical limitations that exist in the implementation process of ML-based RRM strategies, i.e., when developing the corresponding ML model. More specifically:

- *5G datasets unavailability and/or poor quality:* A key procedure for building ML models is the validation and training stage. 5G full deployment throughout the world was set for 2020, before the COVID-19 pandemic. Hence, 5G data from implemented networks have only recently started to be produced. The AI/ML models, that have been produced until now, are using synthetic or incomplete data from past networks' generations [101]. Another aspect that also affects data quality is the fact that, in general, wireless network data are characterized by noise and inaccuracy. In fact, even well-established wireless network datasets -such as DeepMIMO [116]- witness quality issues in a variety of RRM-related problems. We should also keep in mind that, due to the highly interferenced environment, huge datasets, including numerous features and observations, are, anyway, required. All the data-related limitations presented in this paragraph, prevent ML models from reaching high levels of accuracy; lack of input leads to sub-optimal or non-optimal solutions. This consideration reflects every ML-based model, regardless the type of learning. Both supervised, unsupervised, reinforcement or deep learning approaches have insufficient results when the quality of the input data is moderate.
- *Learning difficulties due to channel complexity in multiuser environments:* 5G wireless networks are characterized by multipath propagation in a highly interferenced environment. This, as stated previously, consists one of the reasons for the need for an enormous variety of features and channel observations in ML datasets construction for RRM (preferably Big Data). Hence, feature extraction for channel information becomes a demanding task. Linear models and generic algorithms (such as simple-tree models, regressions, etc.) are unable to provide optimal solutions, concerning effective resource allocation. The approaches discussed in previous sections configure ML-algorithms by alternating hyperparameters and evaluate accuracy in the RRM sub-problems. In this context, performance and models' selection policies are vital in ML-based approaches. Researchers should have deep knowledge of the ML models, pre-trained or not, so that they become able to correctly

evaluate them [117]. Concerning the complexity of the channel and the growing users' demand in 5G/B5G networks, DL methods are proposed as the more efficient ones.

- *Computational complexity:* In terms of accuracy, the AI/ML models discussed in previous sections have improved performance, when used to solve complex problems based on networks' KPIs. Concerning the URLLC requirements and the demand for mass access to the medium in 5G/B5G networks, RRM decision making should be done with respect to computational complexity. However, the highly interferenced environment and random mobility patterns of UEs act in the opposite direction. Thus, ML techniques should succeed in proposing a trade-off between the solution's accuracy and computation requirements [82], [90], [98]. Even though DL solutions are proposed as the most efficient ones, they increase computational complexity, by employing multiple hidden layers to yield accurate results. In this respect, distributed approaches using MEC architectures and FL-based algorithms should be considered. Taking also into account the requirement for energy efficient networks, researchers should maintain the computational cost to tolerable levels [83], [88].

3) Power consumption rapidly increases in 5G, and will further increase in B5G networks, compared to previous generations, due to the users' growing demands for continuous access to enhanced services and applications. ML schemes, if effectively implemented, contribute in power savings, as, hopefully, they lead eventually to fast and more accurate RRM decision-making. For further energy consumption mitigation, we should incorporate energy-efficient technologies during the models' training phase, where additional computational resources are needed. In this direction, Green AI techniques and distributed processing methods (such as MEC) should be further investigated, so that less energy harvesting solutions become feasible [38].

VI. CONCLUDING REMARKS

This article presents a state-of-the-art analysis concerning the deployment of ML-based approaches in the context of efficient RRM in 5G/B5G wireless networks. A categorization of these approaches, based on the type of learning, is provided, in order to point out which ML algorithms should be used in different RRM sub-problems (e.g., unsupervised clustering algorithms in RN selection, DNNs in subcarrier allocation and power management, etc.). Moreover, we emphasize the need for cooperation and coexistence between AI/ML-based RRM and distributed approaches, due to the multiparameter nature of the problem, by presenting MEC and FL as possible solutions, which improve a variety of network and user KPIs. Based on the above, we conclude that ML-enabled approaches can overcome limitations that existing (non-ML) approaches could not, such as non conventionality and real-time integration.

Furthermore, we highlight the open issues and limitations of ML-based RRM and, thus, propose guidelines for other research efforts in the field. In this context, we point out that, 5G datasets unavailability or poor quality, complex channel and high levels of interference, computational complexity and increased energy consumption, are of most importance in the process of building AI/ML models.

Finally, in order to demonstrate effectiveness of ML-based RRM, and also empower the effectiveness of ML algorithms in various RRM sub-problems, we investigate via simulations the problem of throughput prediction, treated either as a regression or as a classification one. According to the presented results, supervised learning approaches (k-NNs, decision trees etc.) overperform in terms of training time, while DL ones overperform in terms of ML performance KPIs (accuracy, F1-score, RMSE, MAE). Results evaluation is consistent with other state-of-the-art approaches.

REFERENCES

[1] C.-X. Wang, F. Haider, X. Gao, X.-H. You, Y. Yang, D. Yuan, H. M. Aggoune, H. Haas, S. Fletcher, and E. Hepsaydir, "Cellular architecture and key technologies for 5G wireless communication networks," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 30–122, Feb. 2014.

[2] M. Agiwal, H. Kwon, S. Park, and H. Jin, "A survey on 4G–5G dual connectivity: Road to 5G implementation," *IEEE Access*, vol. 9, pp. 16193–16210, 2021.

[3] *Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update 2017–2022*, Cisco, San Jose, CA, USA, Feb. 2019.

[4] M. Shafi, A. F. Molisch, P. J. Smith, T. Haustein, P. Zhu, P. De Silva, F. Tufvesson, A. Benjebbour, and G. Wunder, "5G: A tutorial overview of standards, trials, challenges, deployment, and practice," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 6, pp. 1201–1221, Jun. 2017.

[5] T. T. T. Le and S. Moh, "Comprehensive survey of radio resource allocation schemes for 5G V2X communications," *IEEE Access*, vol. 9, pp. 123117–123133, 2021.

[6] S. Penchala, D. K. Nayak, and B. Ramadevi, "Survey on massive MIMO system with underlaid D2D communication," in *Intelligent System Design*. Singapore: Springer, 2021, pp. 453–462.

[7] Y. Mehmood, N. Haider, M. Imran, A. Timm-Giel, and M. Guizani, "M2M communications in 5G: State-of-the-art architecture, recent advances, and research challenges," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 194–201, Sep. 2017.

[8] Q.-V. Pham, F. Fang, V. N. Ha, M. J. Piran, M. Le, L. B. Le, H. Won-Joo, and Z. Ding, "A survey of multi-access edge computing in 5G and beyond: Fundamentals, technology integration, and state-of-the-art," *IEEE Access*, vol. 8, pp. 116974–117017, 2020.

[9] N. T. Le, M. A. Hossain, A. Islam, D.-Y. Kim, Y.-J. Choi, and Y. M. Jang, "Survey of promising technologies for 5G networks," *Mobile Inf. Syst.*, vol. 2016, pp. 1–25, Oct. 2016.

[10] S. K. Goudos, P. I. Dallas, S. Chatziefthymiou, and S. Kyriazakos, "A survey of IoT key enabling and future technologies: 5G, mobile IoT, sematic web and applications," *Wireless Pers. Commun.*, vol. 97, no. 2, pp. 1645–1675, Nov. 2017.

[11] R. Ali, Y. B. Zikria, A. K. Bashir, S. Garg, and H. S. Kim, "URLLC for 5G and beyond: Requirements, enabling incumbent technologies and network intelligence," *IEEE Access*, vol. 9, pp. 67064–67095, 2021.

[12] A. Osseiran, F. Boccardi, V. Braun, K. Kusume, P. Marsch, M. Maternia, O. Queseth, M. Schellmann, H. Schotten, H. Taoka, H. Tullberg, M. A. Uusitalo, B. Timus, and M. Fallgren, "Scenarios for 5G mobile and wireless communications: The vision of the METIS project," *IEEE Commun. Mag.*, vol. 52, no. 5, pp. 26–35, May 2014.

[13] A. Gupta and R. K. Jha, "A survey of 5G network: Architecture and emerging technologies," *IEEE Access*, vol. 3, pp. 1206–1232, 2015.

[14] M. U. Khan, A. Garcia-Armada, and J. J. Escudero-Garzas, "Service-based network dimensioning for 5G networks assisted by real data," *IEEE Access*, vol. 8, pp. 129193–129212, 2020.
[15] R. Dilli, "Analysis of 5G wireless systems in FR1 and FR2 frequency bands," in *Proc. 2nd Int. Conf. Innov. Mech. Ind. Appl. (ICIMIA)*, Mar. 2020, pp. 767–772, doi: 10.1109/ICIMIA48430.2020.9074973.
[16] F. A. Dicandia and S. Genovesi, "Exploitation of triangular lattice arrays for improved spectral efficiency in massive MIMO 5G systems," *IEEE Access*, vol. 9, pp. 17530–17543, 2021.
[17] Y. Niu, Y. Li, D. Jin, L. Su, and A. V. Vasilakos, "A survey of millimeter wave communications (mmWave) for 5G: Opportunities and challenges," *Wireless Netw.*, vol. 21, no. 8, pp. 2657–2676, Nov. 2015.
[18] S. Wijethilaka and M. Liyanage, "Survey on network slicing for Internet of Things realization in 5G networks," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 2, pp. 957–994, 2nd Quart., 2021.
[19] Y. Xu, G. Gui, H. Gacanin, and F. Adachi, "A survey on resource allocation for 5G heterogeneous networks: Current research, future trends, and challenges," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 2, pp. 668–695, 2nd Quart., 2021.
[20] M. Hassan, M. Singh, and K. Hamid, "Survey on NOMA and spectrum sharing techniques in 5G," in *Proc. IEEE Int. Conf. Smart Inf. Syst. Technol. (SIST)*, Apr. 2021, pp. 1–4, doi: 10.1109/SIST50301.2021.9465962.
[21] F. D. Calabrese, L. Wang, E. Ghadimi, G. Peters, L. Hanzo, and P. Soldati, "Learning radio resource management in RANs: Framework, opportunities, and challenges," *IEEE Commun. Mag.*, vol. 56, no. 9, pp. 138–145, Sep. 2018.
[22] A. F. Molisch, V. V. Ratnam, S. Han, Z. Li, S. Le Hong Nguyen, L. Li, and K. Haneda, "Hybrid beamforming for massive MIMO: A survey," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 134–141, Sep. 2017.
[23] Y. Fu, S. Wang, C. Wang, X. Hong, and S. McLaughlin, "Artificial intelligence to manage network traffic of 5G wireless networks," *IEEE/ACM Trans. Netw.*, vol. 32, no. 6, pp. 58–64, Nov./Dec. 2018.
[24] R. Li, Z. Zhao, X. Zhou, G. Ding, Y. Chen, Z. Wang, and H. Zhang, "Intelligent 5G: When cellular networks meet artificial intelligence," *IEEE Wireless Commun.*, vol. 24, no. 5, pp. 175–183, Oct. 2017.
[25] C.-X. Wang, M. D. Renzo, S. Stanczak, S. Wang, and E. G. Larsson, "Artificial intelligence enabled wireless networking for 5G and beyond: Recent advances and future challenges," *IEEE Wireless Commun.*, vol. 27, no. 1, pp. 16–23, Feb. 2020.
[26] *AI and ML—Enablers for Beyond 5G Networks*, 5G PPP Technol. Board, Sophia Antipolis, France, May 11, 2021, doi: 10.5281/zenodo.4299895.
[27] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2224–2287, 3rd Quart., 2019.
[28] I. Alawe, A. Ksentini, Y. Hadjadj-Aoul, and P. Bertin, "Improving traffic forecasting for 5G core network scalability: A machine learning approach," *IEEE/ACM Trans. Netw.*, vol. 32, no. 6, pp. 42–49, Nov./Dec. 2018.
[29] R. Alvizu, S. Troia, G. Maier, and A. Pattavina, "Matheuristic with machine-learning-based prediction for software-defined mobile metro-core networks," *J. Opt. Commun. Netw.*, vol. 9, no. 9, pp. D19–D30, Sep. 2017.
[30] M. H. Abidi, H. Alkhalefah, K. Moiduddin, M. Alazab, M. K. Mohammed, W. Ameen, and T. R. Gadekallu, "Optimal 5G network slicing using machine learning and deep learning concepts," *Comput. Standards Interfaces*, vol. 76, Jun. 2021, Art. no. 103518.
[31] C. Benzaid and T. Taleb, "AI for beyond 5G networks: A cyber-security defense or offense enabler?" *IEEE Netw.*, vol. 34, no. 6, pp. 140–147, Nov./Dec. 2020.
[32] M. Yan, G. Feng, J. Zhou, and S. Qin, "Smart multi-RAT access based on multiagent reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 67, no. 5, pp. 4539–4551, May 2018.
[33] J. Pérez-Romero, J. Sánchez-González, R. Agustí, B. Lorenzo, and S. Glisic, "Power-efficient resource allocation in a heterogeneous network with cellular and D2D capabilities," *IEEE Trans. Veh. Technol.*, vol. 65, no. 11, pp. 9272–9286, Nov. 2016.
[34] S. A. R. Naqvi, H. Pervaiz, S. A. Hassan, L. Musavian, Q. Ni, M. A. Imran, X. Ge, and R. Tafazolli, "Energy-aware radio resource management in D2D-enabled multi-tier HetNets," *IEEE Access*, vol. 6, pp. 16610–16622, 2018.
[35] S. Imtiaz, S. Schiessl, G. P. Koudouridis, and J. Gross, "Coordinates-based resource allocation through supervised machine learning," *IEEE Trans. Cognit. Commun. Netw.*, vol. 7, no. 4, pp. 1347–1362, Dec. 2021.
[36] Y. Guo, F.-C. Zheng, J. Luo, and X. Wang, "Optimal resource allocation via machine learning in coordinated downlink multi-cell OFDM networks under high mobility," in *Proc. IEEE 93rd Veh. Technol. Conf. (VTC-Spring)*, Elsinki, Finalnd, Apr. 2021, pp. 1–7, doi: 10.1109/VTC2021-Spring51267.2021.9448996.
[37] T. E. Bogale, X. Wang, and L. B. Le, "Machine intelligence techniques for next-generation context-aware wireless networks," ICT Discoveries J., Impact Artif. Intell. (AI) Commun. Netw. Services, ITU, Geneva, Switzerland, 2018, no. 1. [Online]. Available: https://www.itu.int/dms_pub/itu-s/opb/journal/SJOURNAL-ICTF.VOL1-2018-1-P13-PDF-E.pdf
[38] D. Lopez-Perez, "A survey on 5G energy efficiency: Massive MIMO, lean carrier design, sleep modes, and machine learning," 2021, *arXiv:2101.11246*.
[39] J. Kaur, M. A. Khan, M. Iftikhar, M. Imran, and Q. E. U. Haq, "Machine learning techniques for 5G and beyond," *IEEE Access*, vol. 9, pp. 23472–23488, 2021.
[40] A. Ly and Y.-D. Yao, "A review of deep learning in 5G research: Channel coding, massive MIMO, multiple access, resource allocation, and network security," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 396–408, 2021.
[41] S. Kayyali, "Resource management and quality of service provisioning in 5G cellular networks," 2020, *arXiv:2008.09601*.
[42] J. H. Joloudari, R. Alizadehsani, I. Nodehi, S. Mojrian, F. Fazl, S. K. Shirkharkolaie, H. M. D. Kabir, R.-S. Tan, and U. R. Acharya, "Resource allocation optimization using artificial intelligence methods in various computing paradigms: A review," 2022, *arXiv:2203.12315*.
[43] B. Brik, K. Boutiba, and A. Ksentini, "Deep learning for B5G open radio access network: Evolution, survey, case studies, and challenges," *IEEE Open J. Commun. Soc.*, vol. 3, pp. 228–250, 2022.
[44] O. Nassef, W. Sun, H. Purmehdi, M. Tatipamula, and T. Mahmoodi, "A survey: Distributed machine learning for 5G and beyond," *Comput. Netw.*, vol. 207, Apr. 2022, Art. no. 108820.
[45] F. Schaich, T. Wild, and R. Ahmed, "Subcarrier spacing—How to make use of this degree of freedom," in *Proc. IEEE 83rd Veh. Technol. Conf. (VTC Spring)*, Nanjing, China, May 2016, pp. 1–6, doi: 10.1109/VTCSpring.2016.7504496.
[46] P.-H. Huang, Y. Gai, B. Krishnamachari, and A. Sridharan, "Subcarrier allocation in multiuser OFDM systems: Complexity and approximability," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Sydney, NSW, Australia, Apr. 2010, pp. 1–6, doi: 10.1109/WCNC.2010.5506244.
[47] S. Oulaourf, A. Haidine, and H. Ouahmane, "Review on using game theory in resource allocation for LTE/LTE-advanced," in *Proc. Int. Conf. Adv. Commun. Syst. Inf. Secur. (ACOSIS)*, Marrakesh, Morocco, Oct. 2016, pp. 1–7, doi: 10.1109/ACOSIS.2016.7843946.
[48] W. Ejaz, S. K. Sharma, S. Saadat, M. Naeem, A. Anpalagan, and N. A. Chughtai, "A comprehensive survey on resource allocation for CRAN in 5G and beyond networks," *J. Netw. Comput. Appl.*, vol. 160, Jun. 2020, Art. no. 102638.
[49] P. K. Gkonis, M. A. Seimeni, N. P. Asimakis, D. I. Kaklamani, and I. S. Venieris, "A new subcarrier allocation strategy for MIMO-OFDMA multicellular networks based on cooperative interference mitigation," *Sci. World J.*, vol. 2014, pp. 1–9, Jan. 2014, doi: 10.1155/2014/652968.
[50] *5G -Study on Channel Model for Frequencies From 0.5 to 100 GHz*, document ETSI TR 138 901 V17.1.0, 2020.
[51] J. Ghosh, V. Sharma, H. Haci, S. Singh, and I.-H. Ra, "Performance investigation of NOMA versus OMA techniques for mmWave massive MIMO communications," *IEEE Access*, vol. 9, pp. 125300–125308, 2021.
[52] V. N. Ha, L. B. Le, and N.-D. Dao, "Cooperative transmission in cloud RAN considering fronthaul capacity and cloud processing constraints," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Istanbul, Turkey, Apr. 2014, pp. 1862–1867, doi: 10.1109/WCNC.2014.6952553.
[53] Z. Wang, H. Li, H. Wang, and S. Ci, "Probability weighted based spectral resources allocation algorithm in Hetnet under Cloud-RAN architecture," in *Proc. IEEE/CIC Int. Conf. Commun. China-Workshops (CIC/ICCC)*, Shanghai, Chine, Aug. 2013, pp. 88–92, doi: 10.1109/ICCChinaW.2013.6670573.
[54] W. U. Rehman, T. Salam, A. Almogren, K. Haseeb, I. U. Din, and S. H. Bouk, "Improved resource allocation in 5G MTC networks," *IEEE Access*, vol. 8, pp. 49187–49197, 2020.
[55] R. D. Mardian, M. Suryanegara, and K. Ramli, "Measuring quality of service (QoS) and quality of experience (QoE) on 5G technology: A review," in *Proc. IEEE Int. Conf. Innov. Res. Develop. (ICIRD)*, Jakarta, Indonesia, Jun. 2019, pp. 1–6, doi: 10.1109/ICIRD47319.2019.9074681.

[56] H. Beshley, M. Beshley, M. Medvetskyi, and J. Pyrih, "QoS-aware optimal radio resource allocation method for machine-type communications in 5G LTE and beyond cellular networks," *Wireless Commun. Mobile Comput.*, vol. 2021, pp. 1–18, May 2021.

[57] N. Wang, Z. Fei, and J. Kuang, "QoE-aware resource allocation for mixed traffics in heterogeneous networks based on Kuhn-Munkres algorithm," in *Proc. IEEE Int. Conf. Commun. Syst. (ICCS)*, Bangkok, Thailand, Dec. 2016, pp. 1–6, doi: 10.1109/ICCS.2016.7833650.

[58] J. Jia, Y. Xu, Z. Du, J. Chen, Q. Wang, and X. Wang, "Joint resource allocation for QoE optimization in large-scale NOMA-enabled multi-cell networks," *Peer-Peer Netw. Appl.*, vol. 15, no. 1, pp. 689–702, Jan. 2022.

[59] R. I. Ansari, H. Pervaiz, S. A. Hassan, C. Chrysostomou, M. A. Imran, S. Mumtaz, and R. Tafazolli, "A new dimension to spectrum management in IoT empowered 5G networks," *IEEE Netw.*, vol. 33, no. 4, pp. 186–193, Jul. 2019.

[60] A. Celik, R. M. Radaydeh, F. S. Al-Qahtani, and M.-S. Alouini, "Joint interference management and resource allocation for device-to-device (D2D) communications underlying downlink/uplink decoupled (DUDe) heterogeneous networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Paris, France, May 2017, pp. 1–6, doi: 10.1109/ICC.2017.7996667.

[61] X. Qi, S. Khattak, A. Zaib, and I. Khan, "Energy efficient resource allocation for 5G heterogeneous networks using genetic algorithm," *IEEE Access*, vol. 9, pp. 160510–160520, 2021.

[62] Y. Xu, Y. Hu, G. Li, and H. Zhang, "Robust resource allocation for heterogeneous wireless network: A worst-case optimisation," *IET Commun.*, vol. 12, no. 9, pp. 1064–1071, Jun. 2018.

[63] R. Liu, Q. Chen, G. Yu, and G. Y. Li, "Joint user association and resource allocation for multi-band millimeter-wave heterogeneous networks," *IEEE Trans. Commun.*, vol. 67, no. 12, pp. 8502–8516, Dec. 2019.

[64] P. Ji, J. Jia, and J. Chen, "Joint optimization on both routing and resource allocation for millimeter wave cellular networks," *IEEE Access*, vol. 7, pp. 93631–93642, 2019.

[65] F. Ye, J. Dai, and Y. B. Li, "Hybrid-clustering game algorithm for resource allocation in macro-femto HetNet," *KSII Trans. Internet Inf. Syst.*, vol. 12, no. 4, pp. 1638–1654, Apr. 2018.

[66] M. Rahman, Y. Lee, and I. Koo, "Energy-efficient power allocation and relay selection schemes for relay-assisted D2D communications in 5G wireless networks," *Sensors*, vol. 18, no. 9, p. 2865, Aug. 2018.

[67] B. Xie, Z. Zhang, R. Q. Hu, G. Wu, and A. Papathanassiou, "Joint spectral efficiency and energy efficiency in FFR-based wireless heterogeneous networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 9, pp. 8154–8168, Sep. 2018.

[68] S. Kim, "4G/5G coexistent dynamic spectrum sharing scheme based on dual bargaining game approach," *Comput. Commun.*, vol. 181, pp. 215–223, Jan. 2022.

[69] M. Bigdeli, S. Farahmand, B. Abolhassani, and H. H. Nguyen, "Globally optimal resource allocation and time scheduling in downlink cognitive CRAN favoring big data requests," *IEEE Access*, vol. 10, pp. 27504–27521, 2022.

[70] T. Pamuklu, S. Mollahasani, and M. Erol-Kantarci, "Energy-efficient and delay-guaranteed joint resource allocation and DU selection in O-RAN," in *Proc. IEEE 4th 5G World Forum (5GWF)*, Oct. 2021, pp. 99–104.

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

[72] T. M. Mitchell, "Does machine learning really work?" *Artif. Intell. Mag., Assoc. Advancement Artif. Intell.*, vol. 18, no. 3, pp. 11–20, fall 1997.

[73] T. M. Mitchell, *Machine Learning*, 1st ed. New York, NY, USA: McGraw-Hill, 1997.

[74] G. Guo, H. Wang, D. Bell, Y. Bi, and K. Greer, "KNN model-based approach in classification," in *Proc. OTM Confederated Int. Conf.* Berlin, Germany: Springer, 2003, pp. 986–996.

[75] C. Jiang, H. Zhang, Y. Ren, Z. Han, K.-C. Chen, and L. Hanzo, "Machine learning paradigms for next-generation wireless networks," *IEEE Wireless Commun.*, vol. 24, no. 2, pp. 98–105, Apr. 2017.

[76] Y. Tang, Y.-Q. Zhang, N. V. Chawla, and S. Krasser, "SVMs modeling for highly imbalanced classification," *IEEE Trans. Syst., Man, Cybern., B, Cybern.*, vol. 39, no. 1, pp. 281–288, Feb. 2009.

[77] A. M. Prasad, L. R. Iverson, and A. Liaw, "Newer classification and regression tree techniques: Bagging and random forests for ecological prediction," *Ecosystems*, vol. 9, no. 2, pp. 181–199, 2006.

[78] M. E. M. Cayamcela and W. Lim, "Artificial intelligence in 5G technology: A survey," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Jeju-Si, South Korea, Oct. 2018, pp. 860–865, doi: 10.1109/ICTC.2018.8539642.

[79] M. E. Morocho-Cayamcela, H. Lee, and W. Lim, "Machine learning for 5G/B5G mobile and wireless communications: Potential, limitations, and future directions," *IEEE Access*, vol. 7, pp. 137184–137206, 2019.

[80] B. Bojović, E. Meshkova, N. Baldo, J. Riihijärvi, and M. Petrova, "Machine learning-based dynamic frequency and bandwidth allocation in self-organized LTE dense small cell deployments," *EURASIP J. Wireless Commun. Netw.*, vol. 2016, no. 1, pp. 1–16, Dec. 2016.

[81] A. Martin, J. Egana, J. Florez, J. Montalban, I. G. Olaizola, M. Quartulli, R. Viola, and M. Zorrilla, "Network resource allocation system for QoE-aware delivery of media services in 5G networks," *IEEE Trans. Broadcast.*, vol. 64, no. 2, pp. 561–574, Jun. 2018.

[82] R. D. A. Timoteo, D. Cunha, and G. D. C. Cavalcanti, "A proposal for path loss prediction in urban environments using support vector regression," in *Proc. Adv. Int. Conf. Telecommun.*, vol. 10. Paris, France, 2014, pp. 119–124.

[83] J. Liu, R. Deng, S. Zhou, and Z. Niu, "Seeing the unobservable: Channel learning for wireless communication networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, San Diego, CA, USA, Dec. 2015, pp. 1–6, doi: 10.1109/GLOCOM.2015.7417805.

[84] H. Zhang, H. Zhang, K. Long, and G. K. Karagiannidis, "Deep learning based radio resource management in NOMA networks: User association, subchannel and power allocation," *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 4, pp. 2406–2415, Oct. 2020.

[85] R. Guerra-Gomez, S. Ruiz-Boque, M. Garcia-Lozano, and J. O. Bonafe, "Machine learning adaptive computational capacity prediction for dynamic resource management in C-RAN," *IEEE Access*, vol. 8, pp. 89130–89142, 2020.

[86] D. Anand, M. A. Togou, and G.-M. Muntean, "A machine learning solution for automatic network selection to enhance quality of service for video delivery," in *Proc. IEEE Int. Symp. Broadband Multimedia Syst. Broadcast. (BMSB)*, Chengdu, China, Aug. 2021, pp. 1–5, doi: 10.1109/BMSB53066.2021.9547176.

[87] M. M. Butt, A. Pantelidou, and I. Z. Kovacs, "ML-assisted UE positioning: Performance analysis and 5G architecture enhancements," *IEEE Open J. Veh. Technol.*, vol. 2, pp. 377–388, 2021.

[88] W. Song, F. Zeng, J. Hu, Z. Wang, and X. Mao, "An unsupervised-learning-based method for multi-hop wireless broadcast relay selection in urban vehicular networks," in *Proc. IEEE Veh. Technol. Conf. (VTC)*, Sydney, NSW, Australia, Jun. 2017, pp. 1–5, doi: 10.1109/VTCSpring.2017.8108458.

[89] L.-C. Wang and S.-H. Cheng, "Data-driven resource management for ultra-dense small cells: An affinity propagation clustering approach," *IEEE Trans. Netw. Sci. Eng.*, vol. 6, no. 3, pp. 267–279, Jul. 2019.

[90] Z. Wang, M. Eisen, and A. Ribeiro, "Unsupervised learning for asynchronous resource allocation in ad-hoc wireless networks," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Toronto, ON, Canada, Jun. 2021, pp. 8143–8147, doi: 10.1109/ICASSP39728.2021.9414181.

[91] M. A. Jamshed, F. Heliot, and T. W. C. Brown, "Unsupervised learning based emission-aware uplink resource allocation scheme for non-orthogonal multiple access systems," *IEEE Trans. Veh. Technol.*, vol. 70, no. 8, pp. 7681–7691, Aug. 2021.

[92] T. M. Getu, W. Ajib, and R. Landry, "A simple F–test based spectrum sensing technique for MIMO cognitive radio networks," in *Proc. 14th Int. Conf. Wireless Mobile Comput., Netw. Commun. (WiMob)*, Limassol, Cyprus, Oct. 2018, pp. 1–8, doi: 10.1109/WiMOB.2018.8589123.

[93] G. Alnwaimi, S. Vahid, and K. Moessner, "Dynamic heterogeneous learning games for opportunistic access in LTE-based macro/femtocell deployments," *IEEE Trans. Wireless Commun.*, vol. 14, no. 4, pp. 2294–2308, Apr. 2015.

[94] G. Han, L. Xiao, and H. V. Poor, "Two-dimensional anti-jamming communication based on deep reinforcement learning," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, New Orleans, LA, USA, Mar. 2017, pp. 2087–2091, doi: 10.1109/ICASSP.2017.7952524.

[95] A. S. G. Spantideas, C. Tsinos, and P. Trakadas, "Power control in 5G heterogeneous cells considering user demands using deep reinforcement learning," in *Proc. Int. Conf. Artif. Intell. Appl. Innov. (IFIP)*. Creta, Greece: Springer, 2021, pp. 95–105.

[96] Q. Qi, A. Minturn, and Y. Yang, "An efficient water-filling algorithm for power allocation in OFDM-based cognitive radio systems," in *Proc. Int. Conf. Syst. Informat. (ICSAI)*, Yantai, China, May 2012, pp. 2069–2073, doi: 10.1109/ICSAI.2012.6223460.
[97] H. Baligh, M. Hong, W.-C. Liao, Z.-Q. Luo, M. Razaviyayn, M. Sanjabi, and R. Sun, "Cross-layer provision of future cellular networks: A WMMSE-based approach," *IEEE Signal Process. Mag.*, vol. 31, no. 6, pp. 56–68, Nov. 2014.
[98] N. Naderializadeh, J. J. Sydir, M. Simsek, and H. Nikopour, "Resource management in wireless networks via multi-agent deep reinforcement learning," *IEEE Trans. Wireless Commun.*, vol. 20, no. 6, pp. 3507–3523, Jun. 2021.
[99] M. Guan, Z. Wu, Y. Cui, X. Cao, L. Wang, J. Ye, and B. Peng, "An intelligent wireless channel allocation in HAPS 5G communication system based on reinforcement learning," *EURASIP J. Wireless Commun. Netw.*, vol. 2019, no. 1, pp. 1–9, Dec. 2019.
[100] Z. Ning, X. Wang, J. J. Rodrigues, and F. Xia, "Joint computation offloading, power allocation, and channel assignment for 5G-enabled traffic management systems," *IEEE Trans. Ind. Informat.*, vol. 15, no. 5, pp. 3058–3067, May 2019.
[101] S. Wang, X. Zhang, Y. Zhang, L. Wang, J. Yang, and W. Wang, "A survey on mobile edge networks: Convergence of computing, caching and communications," *IEEE Access*, vol. 5, pp. 6757–6779, 2017.
[102] J. Poderys, M. Artuso, C. M. O. Lensbøl, H. L. Christiansen, and J. Soler, "Caching at the mobile edge: A practical implementation," *IEEE Access*, vol. 6, pp. 8630–8637, 2018.
[103] T.-V. Nguyen, N.-N. Dao, V. D. Tuong, W. Noh, and S. Cho, "User-aware and flexible proactive caching using LSTM and ensemble learning in IoT-MEC networks," *IEEE Internet Things J.*, vol. 9, no. 5, pp. 3251–3269, Mar. 2022.
[104] A. M. Elbir, "CNN-based precoder and combiner design in mmWave MIMO systems," *IEEE Commun. Lett.*, vol. 23, no. 7, pp. 1240–1243, May 2019.
[105] S. Khalid, W. B. Abbas, and F. Khalid, "Deep learning based joint precoder design and antenna selection for partially connected hybrid massive MIMO systems," 2021, *arXiv:2102.01495*.
[106] C. Zhang, Y. Xie, H. Bai, B. Yu, W. Li, and Y. Gao, "A survey on federated learning," *Knowl.-Based Syst.*, vol. 216, Mar. 2021, Art. no. 106775.
[107] G. Zhu, Y. Wang, and K. Huang, "Broadband analog aggregation for low-latency federated edge learning," *IEEE Trans. Wireless Commun.*, vol. 19, no. 1, pp. 491–506, Jan. 2020.
[108] J. Leng, Z. Lin, M. Ding, P. Wang, D. Smith, and B. Vucetic, "Client scheduling in wireless federated learning based on channel and learning qualities," *IEEE Wireless Commun. Lett.*, vol. 11, no. 4, pp. 732–735, Apr. 2022.
[109] L. Zhao, H. Xu, J. Wang, Y. Chen, X. Chen, and Z. Wang, "Computation–communication resource allocation for federated learning system with intelligent reflecting surfaces," *Arabian J. Sci. Eng.*, vol. 2022, pp. 1–7, Jan. 2022.
[110] A. Iqbal, M.-L. Tham, and Y. C. Chang, "Double deep Q-network-based energy-efficient resource allocation in cloud radio access network," *IEEE Access*, vol. 9, pp. 20440–20449, 2021.
[111] F. Mungari, "An RL approach for radio resource management in the O-RAN architecture," in *Proc. 18th Annu. IEEE Int. Conf. Sens., Commun., Netw. (SECON)*, Jul. 2021, pp. 1–2.
[112] A. Narayanan, E. Ramadan, R. Mehta, X. Hu, Q. Liu, R. A. K. Fezeu, U. K. Dayalan, S. Verma, P. Ji, T. Li, F. Qian, and Z.-L. Zhang, "Lumos5G: Mapping and predicting commercial mmWave 5G throughput," in *Proc. ACM Internet Meas. Conf.*, New York, NY, USA, Oct. 2020, pp. 176–193, doi: 10.1145/3419394.3423629.
[113] D. Minovski, N. Ogren, C. Ahlund, and K. Mitra, "Throughput prediction using machine learning in LTE and 5G networks," *IEEE Trans. Mobile Comput.*, early access, Jul. 26, 2021, doi: 10.1109/TMC.2021.3099397.
[114] L. Alho, A. Burian, J. Helenius, and J. Pajarinen, "Machine learning based mobile network throughput classification," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Nanjing, China, Mar. 2021, pp. 1–6, doi: 10.1109/WCNC49053.2021.9417365.
[115] A. Sharma, S. Pandit, and S. R. Talluri, "A comparative study to classify and predict the throughput of fifth generation wireless technology using supervised machine learning algorithms," in *Proc. 6th Int. Conf. Image Inf. Process. (ICIIP)*, Himachal Pradesh, India, Nov. 2021, pp. 288–292, doi: 10.1109/ICIIP53038.2021.9702678.
[116] A. Alkhateeb, "DeepMIMO: A generic deep learning dataset for millimeter wave and massive MIMO applications," in *Proc. Inf. Theory Appl. Workshop (ITA)*, San Diego, CA, USA, Feb. 2019, pp. 1–8.
[117] L. Xiao, D. Jiang, D. Xu, H. Zhu, Y. Zhang, and H. V. Poor, "Two-dimensional antijamming mobile communication based on reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 67, no. 10, pp. 9499–9512, Oct. 2018.

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