Machine Learning for 5G/B5G Mobile and Wireless Communications: Potential, Limitations, and Future Directions

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ABSTRACT Driven by the demand to accommodate today's growing mobile traffic, 5G is designed to be a key enabler and a leading infrastructure provider in the information and communication technology industry by supporting a variety of forthcoming services with diverse requirements. Considering the ever-increasing complexity of the network, and the emergence of novel use cases such as autonomous cars, industrial automation, virtual reality, e-health, and several intelligent applications, machine learning (ML) is expected to be essential to assist in making the 5G vision conceivable. This paper focuses on the potential solutions for 5G from an ML-perspective. First, we establish the fundamental concepts of supervised, unsupervised, and reinforcement learning, taking a look at what has been done so far in the adoption of ML in the context of mobile and wireless communication, organizing the literature in terms of the types of learning. We then discuss the promising approaches for how ML can contribute to supporting each target 5G network requirement, emphasizing its specific use cases and evaluating the impact and limitations they have on the operation of the network. Lastly, this paper investigates the potential features of Beyond 5G (B5G), providing future research directions for how ML can contribute to realizing B5G. This article is intended to stimulate discussion on the role that ML can play to overcome the limitations for a wide deployment of autonomous 5G/B5G mobile and wireless communications.

INDEX TERMS Machine learning, 5G mobile communication, B5G, wireless communication, mobile communication, artificial intelligence.

I. INTRODUCTION

Machine Learning (ML) is everywhere, from medical diagnosis based on image recognition to navigation for self-driving cars. ML has been evolving as a discipline to the point that it currently allows wireless networks to learn and extract knowledge by interacting with data. Preliminary interest and discussions about the feasibility of evolving 5G standards with the assistance of ML protocols have captured the attention and imagination of engineers and researchers across the globe [1]–[3]. We have witnessed how mobile and wireless systems have become an essential part of social infrastructure, mobilizing our daily lives and facilitating the digital economy in multiple ways [4]. However, ML and 5G wireless communications have somehow been perceived as dissimilar research fields, despite the potential they might have when they are used in combination. In fact, the influence of ML-enabled mobile and wireless network communications has already been made apparent by a number of recent networking paradigms such as location-based services [5], mobile edge caching [6], [7], context-aware networking [8], big data analytics [9], [10], mobile edge computing [11]–[13], and network traffic control [14].

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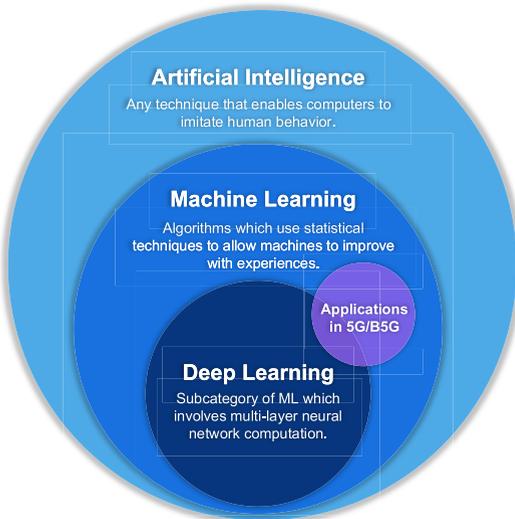
FIGURE 1. Venn diagram of the relation between artificial intelligence, machine learning, and deep learning. This article covers machine learning and deep learning applications in 5G/B5G mobile and wireless communications.

ML is great for complex problems where existing solutions require a lot of hand-tuning, or for problems which there is no solution at all using a traditional approach. These problems can be tackled by learning from data, replacing conventional software containing long rule lists, with ML routines that automatically learn from previous data. An important difference of ML over traditional cognitive algorithms is automatic feature extraction, by which expensive hand-crafted feature engineering can be waived. Broadly speaking, an ML task can detect anomalies, predict future scenarios, adapt to fluctuating environments, get insights of complex problems with large amounts of data, and in general, discover the patterns that a human can miss [15]. Since the notion of ML has matured alongside similar concepts, we illustrate the relation between deep learning (DL), ML, and artificial intelligence (AI) at a high level in Fig. 1.

There are multiple parameters in mobile and wireless networks, and some of them are set using heuristic calculations because no solid closed form solution exists for their value, or because a proper measurement campaign may be prohibitively expensive. For these kinds of problems, an ML algorithm (e.g., a neural network (NN)) can contribute by predicting the parameters and estimating functions based on available data [16]. The next generation of mobile and wireless communication technologies also demands the use of optimization to minimize (or maximize) certain objective functions, and since many problems in mobile and wireless communications are non-linear or polynomial, they have to be approximated. An artificial neural networks (ANN) is an ML technique that can be used to model the objective functions of those non-linear problems that require optimization or approximation [17]. But like any form of technology, ML is not entirely perfect. Among the challenges that are limiting its deployment in wireless communications are the interpretability of results, the difficulty to get relevant data, the computational power required, the complexity
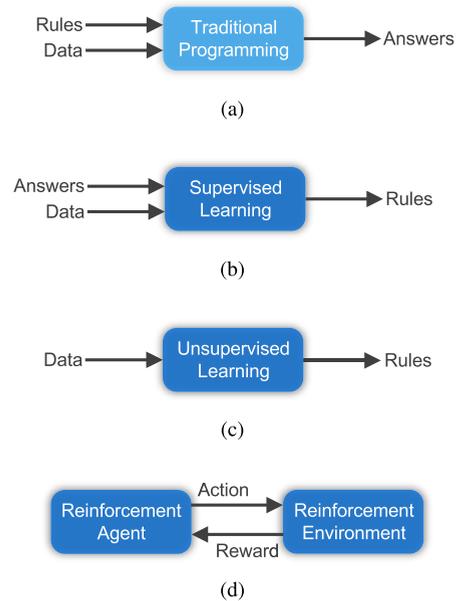

FIGURE 2. Traditional programming compared to the three types of machine learning. (a) Traditional programming, (b) supervised learning, (c) unsupervised learning, and (d) reinforcement learning.

introduced, the long training times of some algorithms, etc. Further applications that fall in the intersection of these fields have been addressed separately for either ML, or wireless communications researchers. Some authors highlighted the potential of ML as an enabler for cellular networks [18], networking functions [19], or radio communications [20]. Nevertheless, there is limited literature evidence on how ML can assist in meeting the specific and practical 5G requirements.

This paper introduces the fundamental concept of ML algorithms and the corresponding 5G applications in accordance with the categories of *supervised learning*, *unsupervised learning*, and *reinforcement learning*. The article is motivated by the vision of intelligent base stations (BSs) making decisions by themselves, mobile devices creating dynamically-adaptable clusters based on learned data rather than pre-established and fixed rules, and mobile networks operating in a fully automated fashion. We raise important issues for future researches to consider, concerning limitations, controversies, and the trade-off between accuracy and interpretability when basic learning algorithms are used as a support to fulfill the diverse requirements of the 5G standard. Finally, this paper analyzes the emerging technologies for B5G together with the contribution opportunities of ML, bringing essential research questions and directions into consideration for this fascinating, yet complex topic.

II. THE THREE TYPES OF LEARNING AND ITS APPLICATION IN WIRELESS COMMUNICATIONS

The article is divided according to the level of supervision that the ML procedure requires on the training stage. The major categories discussed in the following sections are *supervised*, *unsupervised*, and *reinforcement learning*

(See Fig. 2). To understand the difference between these three learning subcategories, a quintessential concept of *"learning"* can be invoked: *"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E"* [35]. Supervised learning comprises looking at several examples of a random vector x and its label value of vector y, then learning to predict y from a completely new x, by estimating $p(y|x)$, or particular properties of that distribution. Unsupervised learning implicates observing different instances of a random vector x and aiming to learn the probability distribution $p(x)$, or its properties. Reinforcement learning comprises an *agent* interacting with an *environment*, and getting feedback loops between the learning system and its experiences, in terms of *rewards* and *penalties* [36].

A. SUPERVISED LEARNING IN 5G MOBILE AND WIRELESS COMMUNICATIONS TECHNOLOGY

In supervised learning, each training example has to be fed along with its respective label. The idea is to train a learning model with samples of the problem with known optima, and then use the model to recognize optimal solutions from new samples. At a high level, the supervised learning problem formulation will have a dataset of instances x (often called training set, examples, samples, or objects), and its corresponding label y. An ML algorithm a_θ (e.g., decision tree, linear model, neural network, etc.) will find a function that maps those instances to labels, as in (1).

$$a_\theta(x) \rightarrow y \qquad (1)$$

To measure the quality of performance of the predictor, the algorithm uses a loss function as follows

$$L(y, a_\theta(x)). \qquad (2)$$

The loss function to use, will depend on the specific application. The main goal of supervised learning is to find the parameters θ', that minimizes the loss function by using the dataset of x and y, as in (3).

$$\theta' \leftarrow argmin_\theta L(y, a_\theta(x)) \qquad (3)$$

Supervised learning tasks are divided into *classification*, and *regression*. Classification is the task of predicting a *discrete* class label output for an input, whilst regression is the problem of predicting a *continuous* quantity output for a given example. A major challenge in supervised learning is that the algorithm should perform properly on new unobserved inputs, not just on the data used for training. This ability is called *generalization* [37]. Typically, when training a supervised model we can compute the error on the training set called the *training error*. The reduction of this error can be described as a naive optimization problem. However, in ML there is also a need of minimizing the *generalization error*, also called the *test error*. The generalization error is defined as the expected value of the error on a new input, and can be

estimated by measuring the performance of the model on the test set.

Underfitting and *overfitting* are other important challenges of supervised learning. Underfitting takes place when the model is not able to obtain a low error on the training set, whereas overfitting occurs when there is a significant difference between the training error and test error [38]. To control whether a model is prone to overfit or underfit, we can adjust its *capacity*, that is, the ability to fit a wide variety of functions. Models with low capacity may struggle to fit the training set, whilst models with high capacity may memorize properties of the training set that will not generalize well on the test set [39]. Insufficient capacity makes a model unable to solve complex tasks, whereas a model with a higher capacity than the needed to solve a simple task has a tendency to overfit. Fig. 3 illustrates how this principle works. ML algorithms perform better when their capacity is proportional to the complexity of the task. The proper level of model complexity is generally determined by the nature of the training data [40]. If we have a small amount of data, or if the data is not uniformly spread throughout different possible scenarios, we should opt for a low-complexity model.
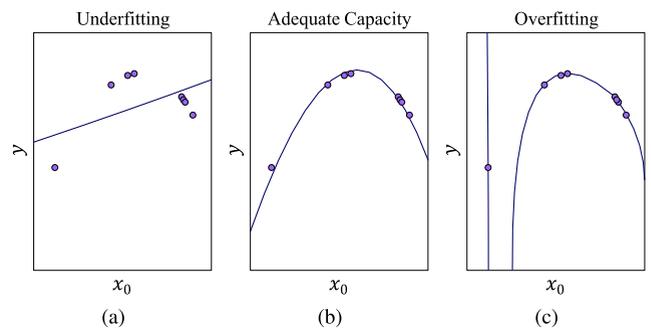

FIGURE 3. An example of training set generated by randomly sampling *x* values and deterministically selecting *y* by evaluating a quadratic function with a low level of noise. (a) A linear function cannot capture the curvature from the data. (b) A quadratic function fits the data properly and is able to generalize well to new points. (c) A polynomial fit passes through all training points very accurately, but it fails to generalize to unseen points from the underlying function.

Dataset shift is another significant challenge in non-stationary environments, where the joint distribution of inputs and outputs changes between training and test stages [41]. A simple strategy to overcome dataset shift, is adapting the parameters of the model accordingly to the changes and retraining the algorithm with an augmented or modified dataset [42]. This adaptation may be done either by the end user [43], [44], or automatically [45], [46]. Fig. 4 illustrates the design of a simple adaptive supervised learning algorithm, and shows how the parameters of the model could be updated to retrain the algorithm by using the feedback from either the testing, validation, or implementation stages. This type of system is trained with multiple examples of a class along with their label, and the model learns how to classify new instances.

The main characteristic that differentiates supervised learning from the other types of learners (unsupervised and
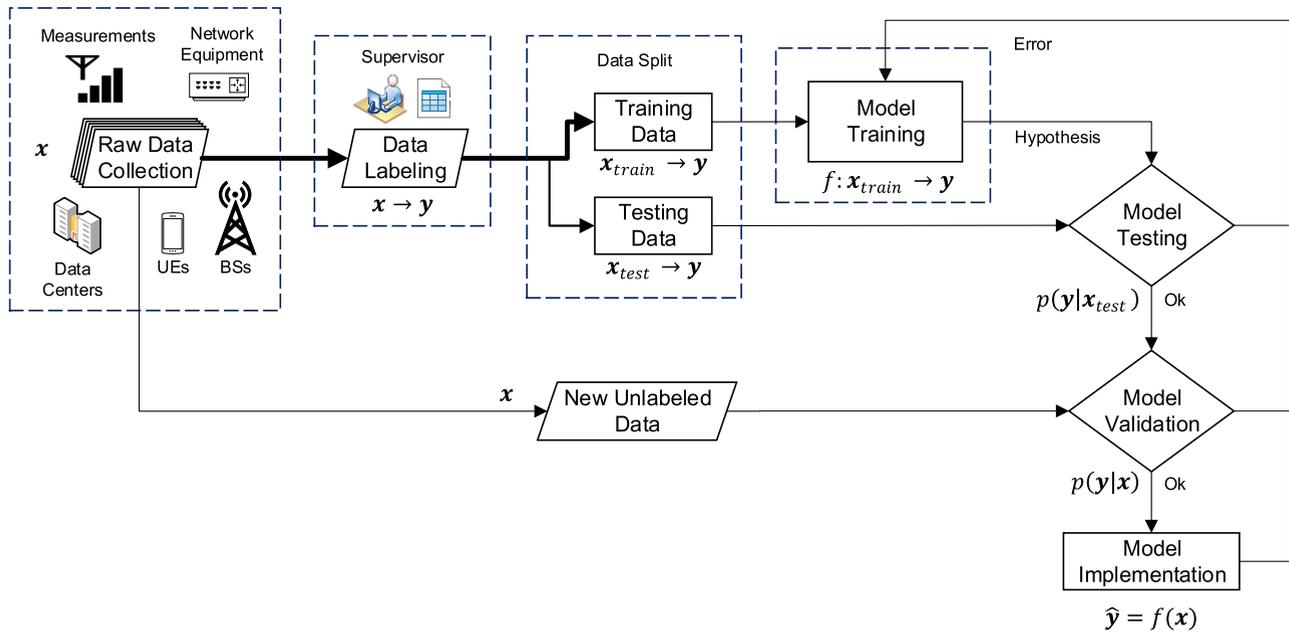
FIGURE 4. The process of automatic adaptation of an ML algorithm to changes. After the raw data has been labeled and splitted, the training data is used for the ML model to learn the patterns/features. The outcomes are subject to evaluation before implementation. After the ML algorithm has been deployed, the errors may be used to correct the model automatically in an iterative manner.

reinforcement) is the initial assumption that we have (or can generate) a dataset of instances with their corresponding labels (x, y). Supervised learning has been beneficial for applications that can access large amounts of data to train their algorithms, as the number of instances directly influences the algorithm robustness. For applications or services that rely on a reduced amount of data, the learning process can be improved through the transfer of knowledge from a related task that has been already pre-trained. Transfer Learning is a popular technique often used to learn the features of any labeled instance, even with a scarce of training data. Essentially, one would train a convolutional neural network (CNN) on a very large dataset, for example on ImageNet [47], and then fine-tune the CNN on a different dataset, with a different vector of features. Fortunately, training on the large dataset is already done by some authors who offer the learned weights for public research use, such as *Alexnet* [48], *VGG Net* [49], or *GoogLeNet* [50].

In 5G networks, LTE small cells are increasingly being deployed to cope with high traffic demands. These small-scale cells are characterized by unpredictable and dynamic interference patterns, expanding the demand for self-optimized solutions that can lead to lower drops, higher data rates, and lower costs for operators. Self-organizing networks (SON) are expected to learn and dynamically adapt to different environments. For the selection of an optimal network configuration in SONs, several ML-based fixes have been discussed. In [22], ML and statistical regression techniques (e.g., bagging tree, boosted tree, SVM, linear regressors, etc.) are evaluated. First, they gathered radio performance measurements such as *path-loss* and *throughput*

for particular frequencies and bandwidth settings from the cells, they later adjusted the parameters using learning-based approaches to predict the performance that a user will experience in the future. The authors showed that the learning-based dynamic frequency and bandwidth allocation (DFBA) prediction methods yielded significant performance gains with *bagging tree* prediction.

Extensive interest in path-loss estimation emerged among researchers when they noticed the power of ML to characterize more efficient and accurate path-loss models, based on publicly available datasets [51]. The use of ML has been proved to provide adaptability to network designers who rely on signal propagation models. Timoteo *et al.* [24], proposed a path-loss prediction model for urban environments using *support vector regression* to ensure an acceptable level of quality of service (QoS) for wireless network users. They employed different kernels and parameters over the *Okumura-Hata* model [52], and obtained results similar to those of a complex neural network, but with lower computational complexity.

Wireless communications actively rely on channel state information (CSI) to make an informed decision in the operations of the network, as well as during signal processing. Liu *et al.* [26], investigated the unobservable CSI for wireless communications and proposed a neural-network-based approximation for *channel learning* to infer this unobservable information from an observable channel. Their framework was built upon the dependence between channel responses and location information. To build the supervised learning framework, they trained the network with channel samples, where the unobservable metrics can be calculated from traditional pilot-aided channel estimation. The applications of

TABLE 1. Summary of Supervised Learning-based proposals for 5G Mobile and Wireless Communications Technology.

ML Technique	Learning Model	Applications in Mobile and Wireless Communication
Supervised Learning	Linear Regression.	Predict and model energy availability to define scheduling policies of harvesting nodes, providing the harvesting node with adaptation to energy availability (as in [21]).
	Statistical Logistic Regression.	Dynamic frequency and bandwidth allocation in self-organized LTE dense small cell deployments (as in [22]).
	Supervised Classifier.	Predict the network demand, to dynamically allocate the amount of network resources, topology setup, and bit rate, according to the connectivity performance i.e., bandwidth, latency, and jitter. (as in [23]).
	Support Vector Machines (SVM).	Path-loss prediction model for urban environments (as in [24]). Classification of the training channel state information (CSI) to select the optimal antenna indices in MIMO (as in [25]).
	Neural-Network-based approximation.	Channel Learning to infer unobservable channel state information (CSI) from an observable channel (as in [26]).
	Probabilistic Learning.	Adjustment of the TDD Uplink-Downlink configuration in XG-PON-LTE Systems to maximize the network performance based on the ongoing traffic conditions in the hybrid optical-wireless network (as in [27]).
	Artificial Neural Networks (ANN), and Multi-Layer Perceptrons (MLPs).	Modelling and approximations of objective functions for link budget and propagation loss for next-generation wireless networks (as in [28]–[32]).
	Deep Neural Networks (DNN).	Prediction and coordination of beamforming vectors at the BSs by learning mapping functions related to the environment setup, by using uplink pilot signals (as in [33]). Channel estimation and direction of arrival (DOA) estimation in MIMO (as in [34]).

their work can be extended to cell selection in multi-tier networks, device discovery for device-to-device (D2D) communications, or end-to-end user association for load balancing, among others. Sarigiannidis *et al.* [27], used a probabilistic learning module over a Software-Defined-Radio-enabled hybrid optical wireless network. The ML framework receives the traffic-aware knowledge from the SDN controllers and adjusts the uplink-downlink configuration in the LTE radio communication. The authors argue that their mechanism is capable of determining the best configuration based on the traffic dynamics from the hybrid network, offering significant network improvements in terms of jitter and latency.

Artificial neural networks (ANN) are a commonly ML architecture used to model or approximate objective functions for existing models or to create accurate models that were impossible to represent in the past without the intervention of learning machines. ANNs have been proposed to solve propagation loss estimation in dynamic environments, where the input parameters can be selected from the information of the transmitter, receiver, buildings, frequency, and so on, and the learning network will train on that data to learn to estimate the function that best approximates the propagation loss for next-generation wireless networks [29]–[32]. In the same context, Ayadi *et al.* [28], proposed a multi-layer perceptron (MLP) architecture to predict coverage for either short or long distance, in multiple frequencies, and in all environmental types. The MLP presented uses feedforward training with back propagation to update the weights of the ANN. They used the inputs of the ITU-R P.1812-4 model [53], to feed their network composed by an input layer, a hidden

layer, and one output layer. They showed that the ANN model predicts coverage in outdoor environments more accurately than the ITU model, using the standard deviation and correlation factor as a comparison measure. Among other ML techniques with potential for wireless communications, there are *k*-Nearest Neighbors, Logistic Regression, Decision Trees, and Random Forests. In Table. 1, we summarize different supervised learning-based models along with the corresponding application in 5G mobile and wireless communications.

B. UNSUPERVISED LEARNING IN 5G MOBILE AND WIRELESS COMMUNICATIONS TECHNOLOGY

In unsupervised learning, the data used to train the ML algorithms is an unlabeled collection of features $x_1, x_2, \ldots, x_n$, and the system attempts to discover subgroups with similar characteristics among the variables, without any guidance. This technique is particularly useful when we want to detect patterns and relationships in the dataset. At no point, the algorithm is told to detect groups of related attributes, as the algorithm solves this connection without intervention. However, in some cases we can select the number of clusters we want the algorithm to create. Clustering is a common ML application that has demonstrated excellent outcomes when grouping edge devices in a mobile network (Fig 5). Autoencoders (AE) have also been part of the historical landscape of NN, and are mostly used for dimensionality reduction, and feature learning [66]. If we apply the concept of AE to the physical layer of a communication system as an end-to-end optimized ML task, the input signal reconstruction
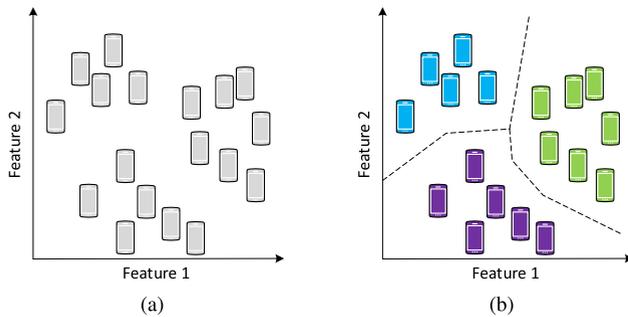
FIGURE 5. Unsupervised learning example. (a) Initial set of unlabeled data with different user equipment distributed along a two-dimensional feature-axis. (b) The instances after being fed into the unsupervised learning algorithm. Notice that the clustering arrangement does not require any supervision.

within a neural network can be studied as a special case of an AE. The optimization of a large non-linear NN with many degrees of freedom for a simple high-level objective has been attempted in [61]. The authors reconstructed a random input message, transmitted and received over a noisy channel. This results bring us closer to a full characterization of the wireless channel, enhancing modeling and maintenance of 5G communications. Balevi *et al.* [59], incorporated fog networking into heterogeneous cellular networks and used an unsupervised soft-clustering algorithm to locate fog nodes to be upgraded from low power nodes (LPNs) to high power nodes (HPNs). The authors showed that by applying ML clustering to *a priori* known data such as the number of fog nodes and the location of all LPNs within a cell, they were able to determine a clustering configuration that reduced latency in the network. The latency calculation was performed with open-loop communications, with no ACK for transmitted packets, and was compared to the *Voronoi* tessellation model, a classical model based on Euclidean distance.

Another typical unsupervised learning technique is *k*-means clustering. Numerous authors have investigated the applications of this particular clustering technique in the next generation wireless network system. Sobabe *et al.* [54], proposed a cooperative spectrum sensing algorithm using a combination of an optimized version of *k*-means clustering, Gaussian mixture model and expectation maximization (EM) algorithm. They proved that their learning algorithm outperformed the energy vector-based algorithm. Song *et al.* [58], discussed how *k*-means clustering and its classification capabilities can aid in the selection of an efficient relay node for urban vehicular networks. The authors investigated different methods for multi-hop wireless broadcasting and how *k*-means can be a key factor in the decision-making of the BSs, by learning from the distribution of the devices and choosing automatically which is the most suitable device to be used as a relay.

When a wireless network experiences unusual traffic demand at a particular time and location, it is often called an *anomaly*. To help identify these anomalies, Parwez *et al.* [55], used mobile network data for anomaly detection purposes

with the help of hierarchical clustering to identify this kind of inconsistency. The authors claim that the detection of these data deviations helps to establish regions of interest in the network that require special actions, such as resource allocation or fault avoidance solutions.

Ultra-dense small cells (UDSC) are expected to increase the capacity of the network, spectrum, and energy efficiency. To consider the effects of cell switching, dynamic interference, time-varying user density, dynamic traffic patterns, and changing frequencies, Wang and Cheng [63], proposed a data-driven resource management for UDSC using *affinity propagation*, an unsupervised learning approach to perform data analysis and extract the knowledge and behavior of the system under complex environments. Later they introduced a power control and channel management system based on the results of the unsupervised learning algorithm. They conclude their research stating that by means of simulation, their data-driven resource management framework improved the efficiency of the energy and throughput in UDSC. Alternative clustering models such as mini-batch *k*-means, mean-shift clustering, DBSCAN, agglomerative clustering, etc., may be used to associate the users to a certain base station (BS) in order to optimize the user equipment (UE) and BS transmitting/receiving power. Table 2, shows a brief summary of the potential applications of unsupervised learning in 5G wireless communication technologies.

C. REINFORCEMENT LEARNING IN 5G MOBILE AND WIRELESS COMMUNICATIONS TECHNOLOGY

Wireless networks operate in stochastic environments under uncertainty (e.g., a node's location and available power level) [100]. In an uncertain environment, the system dynamics can be modelled using a *markov decision process (MDP)* for a mathematical framework modeling to optimize the desired objectives [20]. A learning entity, *agent*, interacts with an environment. At each decision time, the agent chooses an action a available at a current state s. For the action a performed, the system responds by generating a corresponding *reward* or *penalty* (negative reward), $R_{(s,a)}$ and moving into a new state s', as depicted in Fig. 6(a). For a given state s and action a, according to the Markov property, the state transition probability $P_{(s'|(s,a))}$ is independent of all previous states and actions. In the framework of *partially observable MDP (POMDP)* which is a generalized MDP, the agent is not able to observe the state directly, but instead only has partial knowledge while perceiving an observation [101], as shown in Fig. 6(b). Thus, the agent needs to keep track of the probability distribution of the states and the observation probability of the underlying MDP, $O_{(s'|(s,a))}$. The problem described with the MDP framework can be solved by *reinforcement learning (RL)*. The aim of the RL task is finding the best policy, denoted π^*, to maximize the rewards by selecting the most proper action in a given state. The value of a state s under policy π, denoted $V^\pi(s)$ is the expected return when starting in the state s and following π thereafter. The optimal solution V^{π^*} is proved to satisfy the following

TABLE 2. Summary of Unsupervised Learning-based proposals for 5G Mobile and Wireless Communications Technology.

ML Technique	Learning Model	Applications in Mobile and Wireless Communication
Unsupervised Learning	Gaussian Mixture Model (GMM), and Expectation Maximization (EM).	Cooperative spectrum sensing (as in [54]).
	Hierarchical Clustering.	Anomaly/Fault/Intrusion detection in mobile wireless networks (as in [55]).
	k-means Clustering.	Storing the data center contents in clusters to reduce the data travel among distributed storage systems (as in [56]). Optimal handover estimation by clustering the UEs according to their mobility patterns (as in [57]). Relay node selection in vehicular networks (as in [58]).
	Unsupervised Soft-Clustering.	Latency reduction by clustering fog nodes to automatically decide which low power node (LPN) is upgraded to a high power node (HPN) in heterogeneous cellular networks (as in [59]).
	Self-organizing map (SOM) Learning.	Planning the coverage of HetNets with dynamic clusters (as in [60]).
	Autoencoders (AE).	Channel characterization by interpreting a communication system design as an end-to-end reconstruction task, in order to jointly optimize transmitter and receiver components in a single process (as in [61]).
	Adversarial Autoencoders (AAE).	Detecting anomalous behavior in wireless spectrum by using Power Spectral Density (PDS) data in an unsupervised learning setting (as in [62]).
	Affinity Propagation Clustering.	Data-Driven Resource Management for Ultra-Dense Small Cells (as in [63]).
	Non-parametric Bayesian Learning.	Traffic reduction in a wireless network by proactively serving predictable user demands via caching at BSs and users' devices (as in [64]).
	Generative Deep Neural Networks (GDNN)	Capture the presence of traffic correlations that impact the readings of multiple sensors deployed in the same geographical area. (as in [65]).
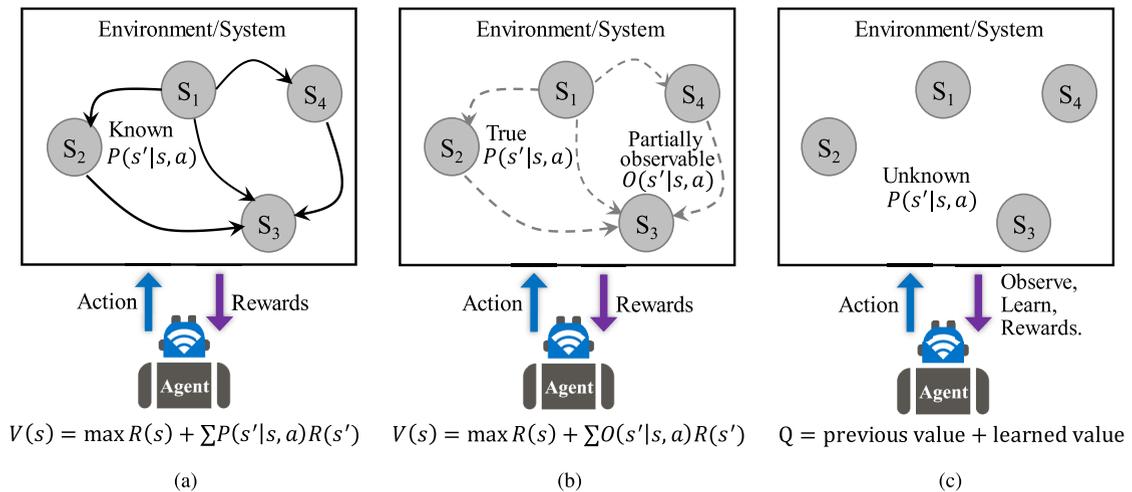
FIGURE 6. Reinforcement Learning: (a) Markov Decision Process (MDP), (b) Partially Observed Markov Decision Process (POMDP), and (c) *Q*-learning [18].

Bellman optimality equation [102].

$$V^{\pi^*}(s) = \max_{a \in A} \sum_{s' \in S} P_{(s'|(s,a))}\left(R_{(s,a)} + \gamma V^{\pi^*}(s')\right), \quad (4)$$

where γ is a discount factor which makes the value of the sum of rewards finite. Equation (4) indicates that the value of a state under an optimal policy is equal to the expected return for the best action in that state. The RL method can be applied to find the best policy π^* in MDP problems. While RL can be applied for the case that an MDP model is available with the *model-based* method, the *model-free*

RL method also can be applied when a MDP model is unknown [103]. Specifically, the agent might not have information on the transition probability and the reward model. In this case, with the model-free RL method, the agent can interact with the environment by exploring the state space and the action space as a trial-and-error learner [104], [105]. One of the popular model-free RL model is *Q-learning* illustrated in Fig. 6(c). According to *Q*-learning, the agent has to estimate a value-function, called *Q*-function, through experience, in order to learn the optimal policy π^* to maximizes the value of total reward. Equation (4) can be rewritten as

follows.

$$V^{\pi^*}(s) = \max_{a \in A} Q^\pi(s, a). \quad (5)$$

The *Q*-learning process turns (5) into an iterative approximation procedure as follows.

$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + \alpha[R(s) + \gamma \max_a Q(s', a)], \quad (6)$$

where α represents the learning rate in which higher the value of α, the greater the agent relies on the reward and the discount future reward, compared to the current *Q*-value. While RL exploits the feedback reward, this feedback is less informative than in supervised learning, where the agent would be given the appropriate actions to take [106], [107] (although such information is not always available). However, it could be more informative than in unsupervised learning, where the agent would be left to find the best actions on its own, without any explicit feedback on its performance [107], [108]. The RL approach has been applied in a variety of schemes such as admission control, load balancing, mobility management, resource management, and dynamic channel selection (DSA) in wireless networks [109]. In a heterogeneous network (HetNet) environment, where various radio access systems coexist and the conditions may change dynamically, adjustment of transmission parameters could be more complicated. Because RL-based algorithms can adapt to a changing environment by learning through their interactions and from the environment, RL has been studied for many algorithms [110] relevant to *load balancing* [70]–[72], [88], *mobility management* [67], [73]–[75], [87], *user association* [76], [77], [99], and *resource allocation* [68], [89], [90].

For traffic load balancing in HetNets, one of the most studied techniques is cell range expansion (CRE), a mechanism to virtually increase a small cell's coverage area by adding a bias value to its reference signal received power (RSRP). In [70], [71], a *Q*-learning based scheme is proposed for the bias value optimization. While the work is about finding an optimal CRE bias value for each device, the authors suggest that the proposed method can reduce the number of outage devices and improve the average throughput compared to non-learning schemes using a common bias value. Simsek *et al.* in [88] integrated decisions of the best bias for CRE with the UE association process. While the proposed algorithm considers UEs' velocity and historical data rate in the short-term scale, results show that the handover failure (HOF) is reduced and the capacity is enhanced. The *multi-armed bandit (MAB)* learning technique has also been exploited. Authors in [72], proposed a *Q*-learning based procedure that integrates a CRE bias value and interference management to improve throughput. However, the proposed approach is difficult to converge, and its optimality cannot be guaranteed [111]. In the works of [67], [73]–[75], [87], the RL approach is applied for the handover decision problem. The authors in [73], [74], [87] focus on maximization of the offered capacity and reduction of the number of unnecessary handover, i.e., by staying in the cell for a long time period.

While *Q*-learning is adopted in [73], [74], the MAB method is exploited in [87]. In the QoE-based handover algorithms proposed in [67], [75], the QoS provided by the chosen network is considered for the reward. A handover decision problem is formulated as an MDP in [67], and *Q*-learning is adopted in [75] to find the optimal handover policy with the aim of maximizing the QoE and minimizing the number of handovers. Though in most studies, mobile devices learn selection decisions through trial-and-error based on a non-cooperative scheme with their dynamic environment, decision making from each device may lead to performance inefficiency from the network side. To overcome this limitation, in [76], the network information is assumed to be provided to help the mobile to make more accurate decisions. Deriving network information is formulated as a *semi-markov decision process (SMDP)* and *Q*-learning is adopted for a radio access technology (RAT) selection algorithm in a network-assisted approach. Nguyen *et al.* [99], also considered a network-assisted approach for a fully distributed RAT selection algorithm including RL. While devices are able to exploit limited network-assisted information provided by the BSs, the framework using RL with network-assisted feedback could contribute in fast convergence time and low signaling overhead. In a multi-RAT environment, devices are expected to be capable of multi-connectivity, i.e., to have access to multiple links over different RATs at the same time. In [77], the algorithm of multiple RATs selection based on multi-connectivity (MC) configuration is proposed. While devices access multiple links for duplicated transmission to enhance reliability performance, the distributed *Q*-learning is applied. By learning the MC configuration condition independently from each UE, results shows that the proposed algorithm can reduce the number of outage devices. To enhance the performance of HetNets, not only cell-specific parameter optimization, such as the CRE bias adaptation, but also resource allocation has been investigated. In [89], the shared resource allocation algorithm for LTE pico cells (PCs) is studied to manage interference. Relying on RL theory, the proposed algorithm helps each cell to select the most suitable sub-channel in an autonomous manner. In [68], resource allocation is approached in a coordinated manner across different tiers. For the packet call admission control problem, the joint radio resource management (JRRM) algorithm is proposed by using SMDP. In a cell shared by two RATs, the spatial distribution of mobile devices and the network traffic load of RATs are considered. Based on user satisfaction integrating the rate and a penalty caused by blocking, the network learns the optimal joint resource management policy to allocate the packet to an appropriate RAT. In [90], a user scheduling and resource allocation scheme for HetNets is proposed to exploit the harvested energy across small cells, and the *actor-critic* method is applied. RL has also been widely applied to studies on cognitive radio networks (CRNs), especially considering the problems in the time-varying dynamics of the wireless environment that cannot be perfectly sensed [69], [91]–[93]. For secondary

networks [112], RL plays an important role in enabling the secondary users (SUs) to autonomously and opportunistically sense the radio environment and tune their transmission parameters in a given environment. Alnwaimi *et al.* [91] proved that self-configuration and optimization using RL can empower femto-cells (FCs) to access the spectrum opportunistically based on learned parameters. While FCs are considered as SUs of LTE macro cells (MCs), with two sequential learning methods, FCs can identify available spectrum opportunities and select subchannels in order to operate under restrictions of avoiding intra/inter-tier interference and to meet QoS requirements. The amount of interference experienced by FCs and the reconfiguration overhead are considered as a *learning cost*. In [92], an anti-jamming strategy for SUs is developed. RL is utilized to choose the frequency channel and determine whether to change its location in the presence of jamming and strong interference. While the learning speed is pointed out as a challenge for a large number of channels and a wide range of signal-to-interference-plus-noise ratio (SINR) levels, this work is improved in [93] in terms of learning rate. In [69], the channel access process of the SUs in a CRN is modelled as a constrained POMDP. While partial observation is assumed to come from the imperfect sensing of SUs over the primary channel state, a reward function is designed for the instantaneous reward of the SUs and a cost function is designed for interference experienced at primary users (PUs). The RL-based algorithm is applied for finding an optimal policy. The applications of ML in CRNs are investigated in [113]. To overcome spectrum scarcity by utilizing the unlicensed spectrum, LTE-Unlicensed (LTE-U) has emerged. The learning approach that accounts for the coexistence of LTE and LTE-U to model the resource allocation problem in LTE-U small stations (SBS), has been studied in [80], [95]. The authors in [95] introduced an RL algorithm based on long short-term memory (RL-LSTM) cells to proactively allocate the resources of LTE-U over the unlicensed spectrum. The problem is formulated as a non-cooperative game between the SBSs, where an RL-LSTM framework enables the SBSs to automatically learn which of the unlicensed channels to use, based on the probability of future changes in terms of the WLAN activity and the LTE-U traffic loads of the unlicensed channels. This work takes into account the value of LTE-U to offload some of LTE data traffic, and the connotation of AI in the form of RL-LSTM for long-term dependencies learning, sequence, and time-series problems. In [80], *Q*-learning is applied for the fair coexistence between LTE and Wi-Fi in the unlicensed spectrum. In the works presented in [78], [79], RL is applied for wireless sensor networks. The authors present a self-organizing RL approach for scheduling the wake-up cycles of nodes based only on their interactions with neighboring nodes. The nodes learn to synchronize when they have to cooperate for forwarding data, and learn to desynchronize in order to avoid intra-network radio interferences. While most works are based on the single-agent RL model, there is a growing interest in its multi-agent extension,

the multi-agent RL (MARL). In MARL, multiple agents, as a group of autonomous and interacting entities, share a common environment and improve their policy iteratively by learning from observations to achieve a common goal [107]. In [96] [97], with the proposed MARL-based channel allocation, it is shown that the transmission and sensing capability for SUs in CRNs could be enhanced. The MARL-based power control strategy proposed in [98] is proved to accelerate the learning of energy harvesting communication systems against intelligent adversaries. Table 3 shows a brief summary of the potential applications of unsupervised learning in 5G wireless communication technologies.

III. POTENTIAL OF MACHINE LEARNING TO SUPPORT 5G REQUIREMENTS

In this section, we look at the road to the next generation network deployment, and explore the link between ML algorithms and 5G requirements [114]. 5G is not an incremental improvement over 4G, but rather the next major evolution of mobile communication with performance improvements of several orders of magnitude over IMT-advanced. The intent of these requirements is to ensure that IMT-2020 guarantees more flexibility, security, and reliability than previous technologies, providing a variety of services and deployment scenarios for a wide range of environments [115], [116]. By agreeing on these requirements, relevant parties (e.g., network operators, manufacturers, regulators, etc.) can work towards developing the same system, where their own particular needs may not be met at the moment. In this section, we have grouped the main 5G requirements into three generic communication services and have studied how ML can assist in reaching their demands. Each service emphasizes a different subset of requirements and applications related to some extent. The three generic services are:

A. ENHANCED MOBILE BROADBAND (eMBB)
Enhancing the current MBB service will enable new applications with higher data rate demands over a uniform coverage area (e.g., ultra-high definition video streaming, and virtual reality) (Fig. 7). The essential requirements to enable eMBB are presented below:

1) PEAK DATA RATE
Peak data rate is planned to increase and support high-demand data-driven use cases. IMT-2020 systems will be required to deliver 20-times higher data rate than the previous technology specification, from 1 Gb/s in 4G to 20 Gb/s in 5G. This is the maximum achievable data rate under ideal error-free conditions assigned to a single mobile station when all of the assignable radio resources for the corresponding link are utilized (excluding radio resources for physical layer synchronization, reference signals, guard bands, etc). An increase of the peak data rate in 5G should be viewed as an evolution that builds on all spectrum assets. The need for new additional spectrum has grown based on the emergence of new use cases, and as communication

TABLE 3. Summary of reinforcement learning-based proposals for 5G mobile and wireless communications technology.

ML Technique	Learning Model	Applications in Mobile and Wireless Communication
Reinforcement Learning	MDP/POMDP.	QoE-based handover decision for HetNets (as in [67]). Packet call admission control in a coordinated manner in HetNets (as in [68]). Channel access process for secondary users in a CRN (as in [69]).
	Q-Learning.	A bias value optimization for cell range expansion (CRE) (as in [70]–[72]). Optimization of handover decision to increase capacity in HetNets (as in [73], [74]). QoE-based handover decision for HetNets (as in [75]). RAT selection algorithm in a network-assisted approach (as in [76]). Multiple RATs selection with multi-connectivity (MC) (as in [77]). Self-organizing scheduling to decide the wake-up cycles of sensors nodes (as in [78], [79]). Fair coexistence issue between LTE and Wi-Fi in unlicensed spectrum(as in [80]). Opportunistic channel access by learning an optimal energy-detection threshold (EDT) (as in [81]). Enable users to select a serving BS by exploiting its local data and the learning outcomes of neighboring users (as in [82]). Find the optimal policy for the cache control unit at the BS (as in [83]). Self-adaptive sleep-scheduling algorithms for wireless nodes and BSs (as in [84]–[86]).
	Multi-armed Bandit.	The capacity optimizer handover decision problem for HetNets (as in [87]). The bias decision for CRE with UE association process (as in [88]). Shared resource allocation for LTE pico cells (PCs) for interference management (as in [89]).
	Actor-Critic.	A user scheduling and resource allocation scheme for the energy harvest across small cells (as in [90]). Enable Femto Cells (FCs) to autonomously and opportunistically sense the radio environment and tune their parameters in HetNets, to reduce intra/inter-tier interference (as in [91]).
	Deep RL.	Anti-jamming strategy for secondary users to decide the communication channel and mobility (as in [92]). Anti-jamming strategy for secondary users to speed up learning rate (as in [93]). Determine the sets of possible connecting neighboring vehicles, and configure the parameters of caching in joint V2V networks [94]. Proactive resource allocation in LTE-U Networks, formulated as a non-cooperative game which enables SBSs to learn which unlicensed channel, given the long-term WLAN activity in the channels and LTE-U traffic loads (as in [95]).
	Multi-agent RL.	Jamming-Resilient Control Channel allocation in CRNs (as in [96], [97]). Power control for energy harvesting communication systems against intelligent adversaries (as in [98]). Heterogeneous Radio Access Technologies (RATs) selection (as in [99]).

FIGURE 7. Enhanced Mobile Broadband (eMBB) applications offers higher peak data rates, and increased wide-area rates.

service providers consider their deployment options for 5G networks, they will need access to significant amounts of spectrum resources to achieve the full performance benefits of the 5G new radio technology. Centimeter waves (cmWave) and millimeter waves (mmWave) are considered to be a

fundamental answer to unlock the full power of eMBB [117]. However, future research should also consider the complex land where multiple frequency bands are subject to different regulations and forms of shared spectrum. Future systems will have to develop flexibility in order to operate across a wide range of regulatory models and sharing arrangements.

Massive or large Multiple-Input Multiple-Output (MIMO) is an essential contribution in the promise to provide an increased spectral efficiency in 5G. MIMO is defined as a system that uses a large number of individually controllable antenna elements to exploit the spatial degrees of freedom of multiplexing messages for several users in the same frequency, or to focus the radiated signal toward intended receivers to minimize intra- and inter-cell interference [118], [119]. Contributions of ML in MIMO technology includes channel estimation and direction of arrival (DOA) estimation by using deep neural networks (DNN) to learn the statistics of the wireless channel and the spatial structures in the angle domain [34]. Another ML contribution in MIMO is the classification of the channel state information (CSI) to select the optimal antenna indices using supervised learning

(i.e., *k*-nearest neighbors (*k*-NN) [120], and support vector machine (SVM) [25]).

2) USER EXPERIENCED DATA RATE

User experienced data rate is defined as the 5% point of the cumulative distribution function (CDF) of the user throughput over active time (i.e., the number of correctly received bits at MAC *Layer 3*), measured in a dense urban environment. IMT-2020 intends to brace 10-times higher user experienced data rate compared to 4G LTE, from 10 Mbit/s to 100 Mbit/s. Its strong connection with other requirements such as *peak data rate* and *latency* makes it ideal to be used as a 5G performance indicator in real-world environments.

Emerging technologies such as wireless network virtualization (WNV) will become one of the main trends in 5G systems and empower a better quality of experience (QoE) for end users [121]. WNV relies on software-defined networking (SDN), and network function virtualization (NFV) to fulfill different network standards [122]. Network programmability via SDNs and NFV offers endless possibilities to aid in the automation of network operation, and management tasks by applying cognitive intelligence and ML algorithms [123], [124]. Network resource allocator systems have been designed based on SDN and NFV to enable autonomous network management. These systems use classifiers to predict the demand and dynamically allocate the amount of network resources, topology setup, and most appropriate bitrate according to the connectivity performance (i.e., bandwidth, latency, and jitter), enhancing the user-perceived data rate [23]. Similarly, ML can be used to dynamically select the most appropriate bit rate according to the connectivity performance, using agents that learn over time. For this case, adequate policy enforcement over the entire network is still an open issue, but it is expected that in the future, multiple SDN controllers can work together in a distributed manner.

By considering the traffic generated by multiple sources, generative deep neural networks (GDNN) can reveal the presence of correlations that impact the readings of multiple sensors deployed in the same geographical area [65]. For example, a GDNN that is fed with the readings of all the sensors of a building may capture correlations that depend on the traffic generated by the devices, making it possible to discriminate not only between different classes of traffic sources (e.g., random warnings, and periodic sensed data), but even between different streams of the same class (e.g., data with higher priority, and temporal trends), due, for instance, to environmental alterations or social phenomena. That kind of rich context information can be further exploited by optimizing the usage of the transmission resources e.g., inferring the type of building (office or residential), and adjusting the propagation models accordingly to maximize the QoE offered to the final user.

3) AREA TRAFFIC CAPACITY

Area traffic capacity refers to the total traffic throughput served per geographic area in Mbit/s/m^2, that is, the number of correctly received bits contained in the service data unit (SDU), over a certain period of time. The target value for area traffic capacity increased from 0.1 Mbits/s/m^2 on IMT-advanced, to 10 Mbit/s/m^2 in 5G.

To handle this area traffic capacity demand, cell densification has been proposed with pleasant results under 5G scenarios [125], [126]. Cell densification refers to the deployment of a large number of small base stations (SBSs) with different cell sizes (i.e., micro, pico, and femtocells), allowing larger spatial reuse of the resources. Additional tiers of small cells provide a tremendous increase in the spectrum reuse factor, which allows the allocation of more bandwidth per UE. Unsupervised learning has been the *de facto* ML-approach for creating clusters in coordinated multi-point (CoMP), based on different features such as capacity improvement, inter-cell interference mitigation, and load balancing [127]. Unsupervised self-organizing map (SOM) learning has also been used for planning the coverage of dynamic clusters in HetNets, with the advantage of adjusting the position of the small cells based on a SON [60]. The major drawback of cell densification is that the traffic that can be served by an SBS is limited by the capacity of the backhaul link. To alleviate the backhaul link congestion and increase connectivity, caching the most popular contents at the network edge has been proposed [128]. Video traffic is particularly suitable to be cached beecause it requires high data rates and exhibits an asynchronous content reuse property [129]. The contents can be cached either at SBSs equipped with a cache memory or at the users' devices directly. One of the most promising technologies to increase traffic capacity is the use of multiple input multiple output (MIMO) and coordinated multi-point (CoMP) antenna systems. Multi-antenna systems in eMBB support extreme-data rates in a given area, by improving spectral efficiency and extreme coverage.

4) SPECTRUM EFFICIENCY

The minimum requirements for peak spectral efficiencies in IMT-2020 are 30 bit/s/Hz for downlink, and 15 bit/s/Hz for uplink. The peak spectral efficiency denotes the maximum data rate under ideal conditions normalized by channel bandwidth (in bit/s/Hz). The available spectrum will extend from 3 GHz in 4G, to 30 GHz in 5G. To meet this requirement, access to flexible techniques that maximize the spectrum efficiency are needed as well. The search for optimal use of the electromagnetic spectrum has led us to think of spectrum use not in terms of exclusive ownership but of multiple access. In the process of accessing the spectrum dynamically, the negative effects of sharing licenses have raised doubts among researchers [130].

To reduce the negative consequences of spectrum sharing on the priority access licenses (PAL) nodes, reinforcement learning has been used in the new 3.5 GHz Citizens Broadband Radio Service (CBRS) band, to access shared spectrum opportunistically. Specifically, a *Q*-learning algorithm was used to adjust the access of the secondary General Authorized Access (GAA) nodes, via learning an
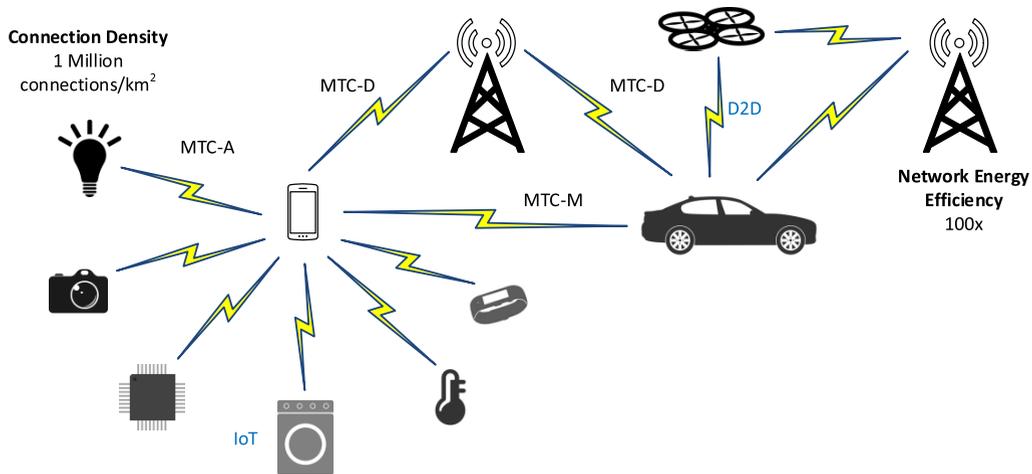
FIGURE 8. Massive Machine Type Communications (mMTC) provides efficient connectivity for the deployment of a massive number of geographically spread devices (e.g., sensors and smart devices). Three access types are planned for mMTC: direct network access (MTC-D), access via an aggregation node (MTC-A), and short-range D2D access (MTC-M).

optimal energy-detection threshold (EDT) for carrier sensing [81]. The local learning framework presented in this work can be extended to a global intelligence using multi-agent learning to jointly optimize within and across different shared-spectrum deployments. Similarly important, detecting anomalous behavior in the wireless spectrum has remained as a critical job due to the complex electromagnetic use of the spectrum. Wireless spectrum anomalies can be significantly different depending on the unwanted signal in a licensed band, which makes manual labeling, an impractical task. This task has now been approached by using adversarial autoencoders (AAE), an ML routine that detects the anomalies in the wireless spectrum by using power spectral density data in an unsupervised learning setting [62].

B. MASSIVE MACHINE-TYPE COMMUNICATIONS (mMTC)
Another key characteristic of 5G communication services is the scalable connectivity demand for the expanding number of wireless network-enabled devices, focusing on the efficient transmission of small payloads over an extended coverage area [131], [132]. Applications such as body-area networks, smart homes, internet of things (IoT), and drone delivery will generate sporadic traffic between a massive number of geographically spread equipments (Fig. 8), requiring mMTC to be able to support new, yet unforeseen use cases. The two central requirements to enable mMTC are:

1) CONNECTION DENSITY
An immense challenge for 5G systems is to connect a massive number of devices to the internet, taking IoT, and smart cities/homes/buildings to a higher level, from 100 thousand connections per km^2 in 4G to 1 million connections per km^2 in 5G. This requirement should be achieved for limited bandwidth and transmission-reception points (TRxPs). The emergence of IoT has given rise to a significant amount of data, collected from sensors, user devices, and BSs,

that must be processed by the next-generation wireless system. The problem of cell association when the density of users increases has been extensively addressed in the past [133], [134], but recently as ML techniques have emerged, Q-learning algorithms have been proposed to enable users to select their serving BS faster by exploiting local data and the learning outcomes of neighboring users, instead of exchanging all the local data among users [82].

Network densification infrastructure (i.e., deploying small femtocells) can easily congest weak backhaul links as well, affecting the QoS of end-users. An ML approach to mitigate this limitation is to fetch popular contents (e.g., video streams) during off-peak hours, storing the data in the SBs' memory units, and reusing them during peak traffic periods [135], [136]. The caching problem has been formulated as a Markov process with an unknown transition probability and is solved using reinforcement learning to find the optimal caching policy to adapt to the underlying dynamics of 5G [83]. In a similar way, ultra-dense networks (UDN) will result in a decrease in the number of active devices per access node, leading UDN to often work under high-load conditions. Novel multiple-access techniques allow overloading the spectrum by multiplexing users in the *power* and *code* domains, resulting in non-orthogonal access. With this approach, gains in user and system throughput of up to 50% can be obtained. Candidate schemes are Non-Orthogonal Multiple Access (NOMA), Sparse Code Multiple Access (SCMA), and Interleave Division Multiple Access (IDMA). These schemes can be combined with open- and closed-loop MIMO schemes [137], [138].

2) NETWORK ENERGY EFFICIENCY
Network energy efficiency is important for eMBB, and it is expected to increase from 1x on 4G, to 100x for IMT-2020. Energy consumption from the devices connected under mMTC applications needs to be considered
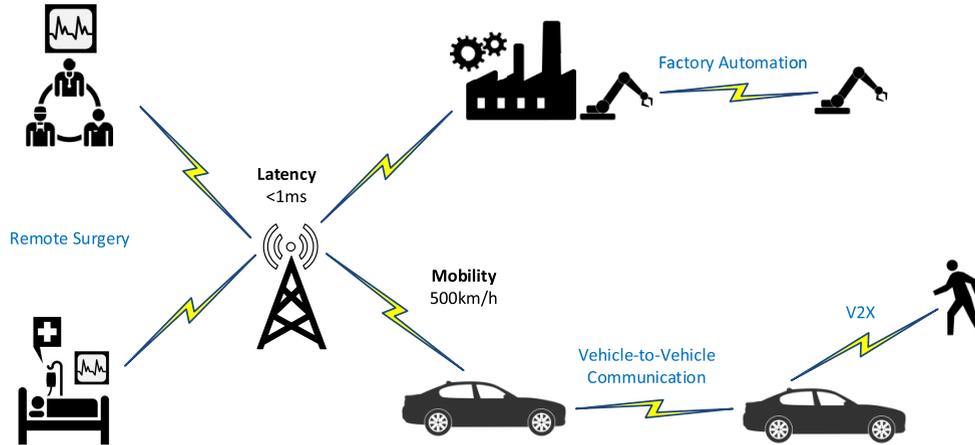
FIGURE 9. Ultra Reliable Low Latency (URLLC) provides ultra-reliable and low-latency communication for demanding applications e.g., V2X, road and traffic safety, factory automation, precision industry, critical health-care communications, etc.

in the future network design due to the new energy-hungry multimedia applications. With a proliferation of wireless devices in 5G applications (e.g., mobile phones, wireless sensors, autonomous vehicles, drones, smart logistics, etc.), energy-efficient wireless networking has been a critical and challenging issue addressed by industry and academia, and will remain a hot research area for a long time [132], [139].

Network energy efficiency is the capability of a RAT to minimize the radio access network energy consumption in relation to the traffic capacity provided. The RAT must have the ability to support a high sleep-ratio and a long sleep duration. This requirement needs to be studied in two sub-aspects: efficient data transmission in a loaded case, and low energy consumption when there is no data. Because the energy of sensor nodes is limited and usually unrechargeable, a fundamental problem that mMTC use cases applications need to solve is the scheduling of sleep and wake-up states of BSs and wireless sensor networks (WSN). The purpose is to keep nodes/BSs in sleep mode as long as possible, maximizing the network energy. Previous techniques such as duty cycling incur a trade-off between energy saving and packet delivery efficiency. Reinforcement learning is helping in the creation of self-adaptive sleep-scheduling algorithms, enabling each node to autonomously decide the optimal operation mode (i.e., transmission, listen, and sleep), through trial-and-error interactions within a dynamic environment [84]–[86].

It is also desirable that the devices connected to mMTC applications integrate energy harvesting technologies. The concepts of ambient energy harvesting from radio frequency (RF) signals and other renewable energy sources are also essential to extend the lifetime of battery constrained devices. To optimize the harvested energy, researchers have used linear regression and decision trees to derive energy prediction models, allowing them to define scheduling policies

and provide the harvesting node with adaptation to energy availability [21].

C. ULTRA-RELIABLE LOW-LATENCY COMMUNICATIONS (URLLC)

Forthcoming network services, e.g., connected healthcare, remote surgery, mission-critical applications, autonomous driving, vehicle-to-vehicle (V2V) communications, high-speed train connectivity, and smart industry applications, will prioritize extreme reliability, low-latency, and mobility, over data rates (Fig. 9). The crucial requirements to enable URLL communications are:

1) LATENCY

Latency is probably one of the most influential performance measures of 5G. A reliable 5G system requires extremely low latency, and even a few milliseconds (ms) can make an enormous difference, making it an extremely important field for 5G researchers and engineers alike. The requirements for IMT-2020 give no room for unbounded delay, from an admissible 10 ms in 4G, to <1 ms in the specification for 5G. Several authors have indicated that ultimately the success of URLLC will rely on an anticipatory network management, capable of predicting the network needs and reacting accordingly [140], [141]. URLLC will be the key to enable real-time connections between autonomous vehicles, e-health, remote robot operation, augmented & virtual reality (AR/VR), etc. As an example, a self-driving car on the road must recognize other vehicles, pedestrians, bikes, and other objects in real-time, not tomorrow.

Latency increases with distance and congestion of network links, which is why not everything can be stored in remote cloud servers away from the final users. The ideal case would be that the local BS always has the desired content. If it does not, the user will have to download it from a cloud server very far away, increasing the latency

proportionally [142], [143]. In the other hand, BSs have limited storage size, so they have to learn to predict user needs. ML-based solutions (e.g., *Q*-learning, deep policy gradient, non-parametric Bayesian learning, etc.) have yielded good results for content popularity prediction and caching [6], [7], [9], [83], [94].

Peak traffic demands can be substantially reduced by proactively serving predictable user demands via caching at BSs and users' devices. Researchers have obtained significant improvements in the context of edge caching just by applying off-the-shelf ML algorithms, such as *k*-means clustering and non-parametric Bayesian learning [64]. Because of the massive amounts of data in future 5G networks, it would be much more efficient to fragment big servers into multiple smaller ones to run computations in parallel. With these tools, every BS will be able to store a reduced but adequate set of files or contents. This is one example of why our future networks must be predictive, and how ML becomes crucial in optimizing this type of problems. By deploying simple ML tools such as *k*-means clustering, ML can assist in partitioning the data center contents in blocks before storage, reducing the data travel among distributed storage systems and contributing significantly to latency reduction [56]. So far ML has been focused on running algorithms in a centralized manner, without caring about latency issues. Interesting future work would investigate the use of distributed mini-servers with storage and computing capabilities, instead of using a centralized cloud server, proactively referring to the BSs that serve users.

2) MOBILITY
Mobility is described as the maximum mobile station speed at which a defined QoS can be achieved (in km/h). For the high-speed vehicular mobility scenario, it is assumed that the user is moving at the maximum speed of 500 km/h, as opposed to the previous 350 km/h on 4G. To support these highly-mobile use cases, particularly in dense mmWave deployments where the users need to frequently hand-off between BSs, an optimal identification of the beamforming vectors is essential. ML models can use the uplink pilot signal received at the terminal BSs, and learn the implicit mapping function relating to the environment setup to predict and coordinate beamforming vectors at the BSs [33]. In a similar vein, smarter mechanisms in which SBSs need to coordinate to do joint load balancing and content sharing are also required. Mechanisms for handover control in wireless systems using ML have been proposed previously, where the centralized controller clusters the UEs according to their mobility patterns (i.e., speed information, locations of the UEs, geographic context, as well as past trajectories) using unsupervised learning in order to obtain an optimal handover policy for each UE [57].

Mobility-aware network design also plays an important role in the joint communication between high-mobility networks. Deep *Q*-learning has been suggested to determine the sets of possible connecting neighboring vehicles, as well as to configure the parameters of caching placement [94].

Additional promising uses of ML to leverage the mobility of wireless networks includes feature extraction or pattern recognition to identify, predict, and mitigate interference in flexible network deployments such as mobile relay nodes or nomadic nodes. Mobile networking is one of the most critical technologies for 5G mobile communications, but fortunately, an anticipatory mobility management through ML is opening a new road towards URLL networking. Fig. 10 shows a concise summary of the applications of ML in the IMT-2020 requirements.

IV. BEYOND 5G, EMERGING TRENDS AND OPPORTUNITIES
While 5G is being rolled out in different parts of the world, Beyond 5G systems (B5G) have gained significant interest and several research projects have recently started exploring B5G or the sixth generation (6G) systems [144], [145]. In this section, considering the promising features of B5G, the contributions of ML are investigated for B5G. In B5G, the emergence of multi-service communication is expected. As opposed to the fixed service categorization into eMBB, mMTC, uRLLC classes in 5G, some applications in B5G may demand dynamic and/or multiple service-type allocation [146]. For the services in fixed categories, they are expected to be sophisticated, increasing the network complexity. While the reliability and latency requirements in 6G could be use case specific, the most extreme values could be 10^{-9} and 0.1 ms, respectively, corresponding to the requirements in Industry 4.0 applications [144]. For the device density, 3D connectivity will be an important consideration [147]. With the 5G requirement of a million devices per km^2, the network is anticipated to support about 10 devices per m^2 and 100 devices per m^3 in 6G [146]. In terms of energy efficiency, authors in [148] expect that 6G will support ultra-long battery life to remove the need of carrying charging devices. Considering the ever-increasing network complexity and emergence of multi-service applications, it would be essential to enhance the network intelligence to realize self-organizing features. That is, the network monitors changes in the environment and estimates uncertainties, and the network then uses those monitoring results for network re-configuration. In addition to self-organizing parameters, from multiple perspectives, such as auto-building the network slices for emerging services and sufficient flexibility for network maintenance, it is essential for networks to observe environment variations, learn uncertainties, plan response actions, and adjust the network configurations accordingly [18]. ML has actually been long exploited for self-organization [149]. In B5G, ML is considered as a key element in the design of the network to be more autonomous, self-organizing and dynamic [147].

5G will only arrive gradually to our lives, yet future researchers should start looking at what 5G will leave on the table. Even though it may seem early to talk about a 6G technology, we shall stay updated and focus on the emerging
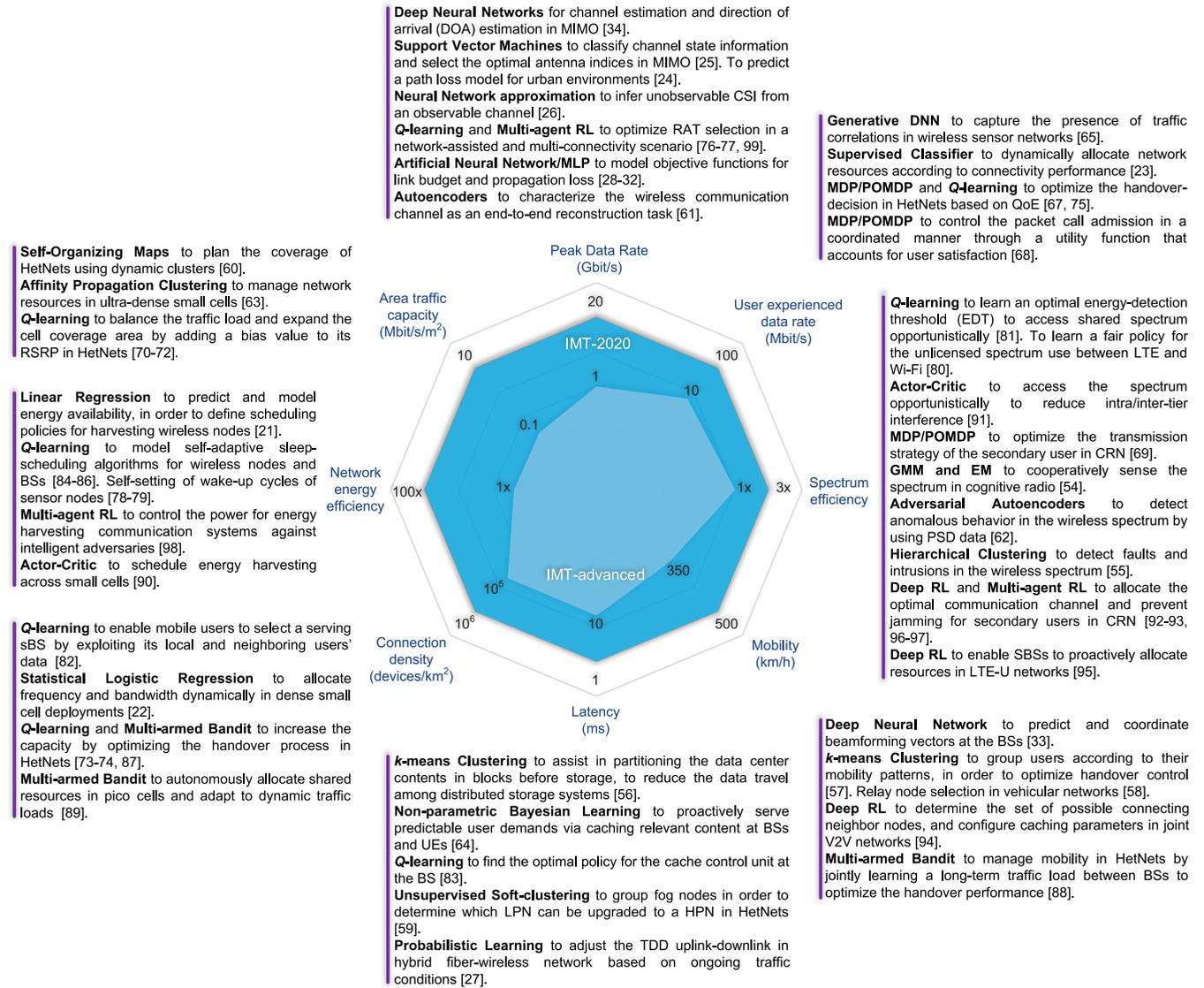
Deep Neural Networks for channel estimation and direction of arrival (DOA) estimation in MIMO [34].
Support Vector Machines to classify channel state information and select the optimal antenna indices in MIMO [25]. To predict a path loss model for urban environments [24].
Neural Network approximation to infer unobservable CSI from an observable channel [26].
Q-learning and **Multi-agent RL** to optimize RAT selection in a network-assisted and multi-connectivity scenario [76-77, 99].
Artificial Neural Network/MLP to model objective functions for link budget and propagation loss [28-32].
Autoencoders to characterize the wireless communication channel as an end-to-end reconstruction task [61].

Generative DNN to capture the presence of traffic correlations in wireless sensor networks [65].
Supervised Classifier to dynamically allocate network resources according to connectivity performance [23].
MDP/POMDP and **Q-learning** to optimize the handover-decision in HetNets based on QoE [67, 75].
MDP/POMDP to control the packet call admission in a coordinated manner through a utility function that accounts for user satisfaction [68].

Self-Organizing Maps to plan the coverage of HetNets using dynamic clusters [60].
Affinity Propagation Clustering to manage network resources in ultra-dense small cells [63].
Q-learning to balance the traffic load and expand the cell coverage area by adding a bias value to its RSRP in HetNets [70-72].

Linear Regression to predict and model energy availability, in order to define scheduling policies for harvesting wireless nodes [21].
Q-learning to model self-adaptive sleep-scheduling algorithms for wireless nodes and BSs [84-86]. Self-setting of wake-up cycles of sensor nodes [78-79].
Multi-agent RL to control the power for energy harvesting communication systems against intelligent adversaries [98].
Actor-Critic to schedule energy harvesting across small cells [90].

Q-learning to enable mobile users to select a serving sBS by exploiting its local and neighboring users' data [82].
Statistical Logistic Regression to allocate frequency and bandwidth dynamically in dense small cell deployments [22].
Q-learning and **Multi-armed Bandit** to increase the capacity by optimizing the handover process in HetNets [73-74, 87].
Multi-armed Bandit to autonomously allocate shared resources in pico cells and adapt to dynamic traffic loads [89].

Q-learning to learn an optimal energy-detection threshold (EDT) to access shared spectrum opportunistically [81]. To learn a fair policy for the unlicensed spectrum use between LTE and Wi-Fi [80].
Actor-Critic to access the spectrum opportunistically to reduce intra/inter-tier interference [91].
MDP/POMDP to optimize the transmission strategy of the secondary user in CRN [69].
GMM and EM to cooperatively sense the spectrum in cognitive radio [54].
Adversarial Autoencoders to detect anomalous behavior in the wireless spectrum by using PSD data [62].
Hierarchical Clustering to detect faults and intrusions in the wireless spectrum [55].
Deep RL and **Multi-agent RL** to allocate the optimal communication channel and prevent jamming for secondary users in CRN [92-93, 96-97].
Deep RL to enable SBSs to proactively allocate resources in LTE-U networks [95].

Deep Neural Network to predict and coordinate beamforming vectors at the BSs [33].
k-means Clustering to group users according to their mobility patterns, in order to optimize handover control [57]. Relay node selection in vehicular networks [58].
Deep RL to determine the set of possible connecting neighbor nodes, and configure caching parameters in joint V2V networks [94].
Multi-armed Bandit to manage mobility in HetNets by jointly learning a long-term traffic load between BSs to optimize the handover performance [88].

k-means Clustering to assist in partitioning the data center contents in blocks before storage, to reduce the data travel among distributed storage systems [56].
Non-parametric Bayesian Learning to proactively serve predictable user demands via caching relevant content at BSs and UEs [64].
Q-learning to find the optimal policy for the cache control unit at the BS [83].
Unsupervised Soft-clustering to group fog nodes in order to determine which LPN can be upgraded to a HPN in HetNets [59].
Probabilistic Learning to adjust the TDD uplink-downlink in hybrid fiber-wireless network based on ongoing traffic conditions [27].

FIGURE 10. Requirements of IMT-2020 compared against previous IMT-Advanced demands, and a brief summary of its corresponding ML-driven approaches to cope with the demand of the 5G standards.

trends to be able to steer the wheel of our research if it is needed.

The first thing that comes into mind when envisioning any future generation network is a *higher bit rate*, which heavily depends on the available electromagnetic spectrum. Finding yet more usable frequencies in the current crowded spectrum will remain as one of the main challenges beyond 5G. The actual use of mmWave frequencies to gain access to new spectrum at higher frequency bands has defined a new era of wireless communications [150], [151]. Nevertheless, a subsequent expansion into *sub-millimeter waves* beyond 5G will bring new research opportunities on the effects of *propagation*, *attenuation*, and *channel modeling* for these new bands since EM waves are easily blocked by dense structures, the position of the hand on the device, and even weather conditions at these higher frequencies [152], [153].

In the future all new spectrum is going to be shared, and as a consequence, the research of dynamic use of different frequencies comes into play. Imagine if a network operator is running out of spectrum, instead of blocking additional users' connections, they could use the inactive spectrum from another operator by listening and checking if the other operator's spectrum is free (which most of the time is). This cognitive and cooperative *spectrum sharing* approach comes with a manifold of research opportunities, and of course ML is predicted to play a big part in solving a new variety of challenges, including the maximization of the utilization of unlicensed spectrum, adaptive smart-contracts, opportunistic exploitation of white spaces, adaptive leasing between carriers, and so on [81], [154], [155]. It is important to notice that each carrier has different traffic patterns, so they can be easily be distinguished and classified by an

ML algorithm. The same methodology applies for the Wi-Fi spectrum.

There has been also a strong expectation regarding the *antenna technology* design for the mmWave and above bands [156]–[158]. However, to access those promising bands above 30GHz, smaller and *adaptive antennas* need to be designed and installed in the upcoming mobile devices to receive the higher frequency waves. ML could help in the operation of future millimeter antennas by making them adaptable to specific scenarios based on available data from the environment, signal strength, user positioning, etc. Interesting work has been done using *metamaterials* to guide surface waves and cloak antennas between each other at certain frequency bands [159]–[162]. This technology could allow to pack a massive number of antennas more tightly than would be traditionally possible. It is envisioned that ML-based metamaterial antennas will be embedded on small chip in handsets and small cells in the near future.

In addition, *future applications*, such as Tactile Internet, the Internet of Skills, autonomous vehicles, and Virtual Reality will become a must-support application by the time the next standardization takes place, pushing the higher individual data rates and low latency more than any other application we know of so far. Applications such as smart city, e-healthcare, and factory 4.0 will finally extend IoT to the *internet of everything (IoE)*, emphasizing machine-to-machine (M2M), machine-to-people (M2P) and technology-assisted people-to-people (P2P) communications. ML will have a leading role as a technique to manipulate the data generated by IoE devices, giving meaning to information in order to produce useful insights. These applications will require additional infrastructure, but certainly they will force the network beyond 5G at some point. Several authors have pointed towards the possibility that 6G will be the first standard of cellular designed primarily for *M2M* communication, heavily impacting the requirements for QoS and roaming. As the number of connected devices increases, an accurate positioning technique will be required as well. Small cell data can be used to train ML algorithms to infer the positions of network users' equipment (e.g., inside a building), by using the received signal strengths from each cell. This information can be later used to predict the location of a device, helping deliver wireless service closer to where customers are physically located.

An additional trend that has proven to perform well is the enhancement of the current state of spatial multiplexing angle with *massive* MIMO technology, allowing BSs to accurately direct the beams to individual users. Even so, there is much left to be done in spatial bandwidth enhancement beyond the current massive MIMO offerings. ML could perfectly assist the scheduling of beams and configure channels in massive MIMO (e.g., training a neural network to predict the best scheduling strategy on demand). Some studies assumes that the user equipment connects to a single cell, but it is envisioned that *distributed* massive MIMO allows us to connect to several cells, getting better performance. The operator can tune the network using ML to improve the network experience for every user. It is easy to see how we could get more capacity on the edge of a cell by connecting to a neighboring cell. These and just a few optimization examples that are becoming possible as the network is controlled by a centralized RAN.

The size configuration of an uplink control channel (which transmits feedback on network quality), also uses spectrum, meaning that there are fewer resources available for data transmission. It is a very important problem as we go to 5G, given that the uplink control channel data will be more contaminated with other control signals (e.g., information on the beams in a massive MIMO network). An ML system could predict user equipment characteristics, such as mobility and traffic demand, and predict what the uplink/downlink data rates would be against different settings, and choose the optimal one.

On a different line, the evolution of 5G will require a global collaboration, including worldwide mobile communication companies and local governments. A lineal correlation between the industry production and ML investment has already been proven [163], [164], and it seems that the integration of ML in the development of forthcoming technology will return an extension of compatibility with subsequent services and requirements. It would be expected that ML will be fully integrated into an intelligent network system in time for 6G. That being said, an important question needs to be raised: *can 6G survive without ML?* Clearly, the dynamism of today's data forces ML to be a necessity for many technology designs. Still, the industry has yet to properly come to grips with how to measure the true benefit of ML, leaving many great technologies waiting to be properly motivated for production. A future 6G technology might seem a lot like an extension of 5G right now, but as new technologies continue to emerge, especially in ML, materials, antenna integration, and so on, there is room for fundamental radio and network improvements. The path to a next generation network can feel uncertain without a given specification, but thinking ahead will put us in a position where we can see a world of opportunities for prospective research topics, where others just see drawbacks and difficulties.

V. SPECIAL CONSIDERATIONS TO DEPLOY ML ON 5G AND B5G

Bringing ML into 5G production incurs a unique set of challenges that needs to be addressed and understood before starting any project or research. Even though a full outline of the concerns in ML is beyond the scope of this article, we thoughtfully introduce the most prevailing ones.

A. THE CRITICAL ROLE OF DATA

High-quality data is an essential piece in ML applications, and the type of data (i.e., labeled, or unlabeled) is a key factor when deciding which type of learning to use, especially when it comes to deploying applications for 5G use cases.

In the matter of wireless communications, it is important to notice that generating a dataset from computer simulators is not always the best practice since the ML algorithm will end up learning the rules with which the simulator was programmed, and this will not reflect the un-observable features from the real world (remember that the point is learning from real data). The scarcity of real datasets available for 5G mobile and wireless communications is one of the biggest challenges for researchers and ML practitioners. For many wireless problems, researchers work closely with domain experts to formulate the best representation of their data. This is called *feature engineering*, and usually takes plenty of effort and insights. For other cases, the need for manual feature engineering can be waived by ML automated feature learning, especially in larger systems. This technique is called *feature learning* or *representation learning*, and it operates by feeding-in all data and letting the algorithm discover which features have the most relevance [165]. Certain wireless systems have the need to update and analyze the datasets simultaneously. This issue has been tackled by using online learning to update the predictors in steps [166].

Telecommunication industries that generate an immense amount of data every day, safeguard this information as one of their most valuable business assets. Consequently, 5G research groups, academics, and key industry partners are defining and developing 5G infrastructure to generate their own datasets for research [167]–[171]. For example in [172], a wireless network data resource is open for the research community. This archive stores wireless trace data from many contributing locations to develop ML algorithms and analyze the data.

B. THE NO FREE LUNCH THEOREM

The *No Free Lunch Theorem* in ML establishes that if we average all possible data-generated distributions, every ML algorithm will have the same performance when inferring unobserved data [173]. Otherwise stated, no ML algorithm is universally better than any other. These results hold when we average over all possible data generating distributions in real world applications. This means that the goal of ML is not to seek the absolute best learning algorithm. Instead, we need to understand what kind of distribution is relevant to our specific 5G/B5G application, and which ML algorithm has the best performance on that specific data.

C. HYPERPARAMETERS SELECTION

Most ML algorithms have values that are set before the training begins. These settings are called *hyperparameters* because their choice influences the eventual *parameters* (i.e., the coefficients or weights) that are updated from the learning outcomes [174]. For instance, in the case of polynomial regression, the *learning rate* hyperparameter influences how fast the model converges in its search of the optimal weights, and the *capacity* hyperparameter controls the degree of the polynomial [175] (as explained in Fig. 3). In the case of unsupervised learning, we can define the *distance function*

or *density threshold* hyperparameters for a certain cluster analysis [176]. In the case of RL the values of *number of averaged experiment trials*, or the *environmental characteristics* are considered as the hyperparameters that control the learning process [177]. In the case of DNN, there are many other choices such as the *number of layers*, the *number of neurons* in each layer, the *batch size* to use during training, etc. If an ML algorithm produces excellent results in one problem space, it might not be as effective or insightful in another field (e.g., mobile, and wireless communications). Researchers that start from a solution that worked in another context, often find themselves making significant modifications and improvements before they start getting results [178]. Accordingly, the probability that we might need to handcraft a custom ML algorithm to tackle a novel 5G problem, is still high.

D. INTERPRETABILITY VS. ACCURACY TRADE-OFF

After deploying an ML algorithm in a given 5G scheme, we would like to know why a BS allocates more network resources to a given user than the other, or why a specific RAT is selected to connect certain UEs in HetNets. From a stakeholder standpoint, these complex interactions between the independent variables are difficult to understand and might not always make business sense [179]. To explain why a certain model is best suited in a particular situation and how the selection of the algorithm is related to the given use case, a depth understanding of the trade-off between *accuracy* and *interpretability* becomes convenient (Fig. 11).
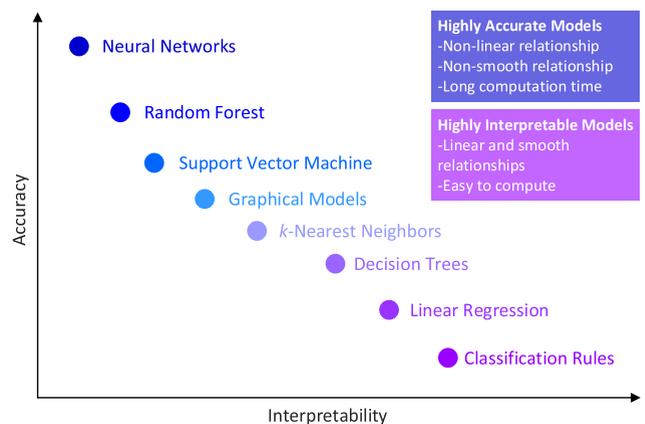
FIGURE 11. The trade-off between interpretability and accuracy of some relevant ML models. Highly interpretable algorithms such as classification rules, or linear regression, are often inaccurate. Very accurate DNNs are a classic example of black boxes.

Depending on the application, our goal would be to find the right balance in a model that provides both good accuracy with high interpretability.

To be able to interpret DNN models it is essential to understand the functionality of the different hidden layers, and how nodes are activated. Segmenting a network by grouping interconnected neurons will provide a simpler level of abstraction to understand its functionality [180].

Understanding how DNN forms individual concepts that can then be assembled into the final output is another key for building interpretability. Either way, when implementing DL models, there could be a price to pay in terms of accuracy.

E. PERFORMANCE METRICS

In order to determine how well an ML algorithm will work when deployed in a real scenario, it is important to measure its performance on unseen/unlabeled data. Generally, the performance measure is specific to the task being carried out by the system. For tasks such as classification, the *accuracy* of the model is used as a measure of performance. Accuracy is defined as the percentage of samples for which the algorithm produces a correct output [181]. We can also obtain performance information by measuring the *error rate*, the proportion of examples for which the model produces an incorrect output. For these purposes, we evaluate these performance measures using a test set of data that is separate from the data used for training the ML system. The choice of performance measure may seem straightforward and objective, but it is often difficult to decide what should be measured.

For unsupervised learning tasks, such as density estimation, we should use a different performance metric that can give the model a continuous-valued score for each example. The most common approach is to report the average *log-probability* that the model assigns to some example [182].

Theoretically, RL algorithms come with a provable guarantee of asymptotic convergence to optimal behavior [183]. In practical terms, the agent quickly reaches a plateau at 99% of optimality for most applications. Optimality is usually an asymptotic result, therefore, *convergence speed* is an imprecise performance metric [184]. An appropriate performance measure may be obtained by evaluating the expected decrease in reward gained due to executing the learning algorithm, instead of behaving optimally from the beginning. This measure is known as *regret* [185], and penalizes mistakes that occur during the learning process.

F. PRIVACY AND SECURITY

The ability of ML to swiftly overcome to changing situations has enabled it to become a fundamental tool for computer security, intrusion detection, and cyber-physical attacks on mobile and wireless communications [186]. Ironically, that adaptability is also a vulnerability that may produce unexpected results in the network [187]. For instance, a CNN can be easily deceived by malicious designed noised images [188], or the agents in RL may be tricked to find unsuitable ways to increase the reward delivered by their interacting environment [189]. One of the limitations of ML algorithms in practice is that they might be subject to adversarial attacks, that is, an input sample can be modified to force a model to classify them in a category different from their genuine class [190]. In practice, *model resilience* (i.e., the robustness of a model to perturbations on its inputs) can be achieved by requiring higher confidence in the outputs (i.e., moving the decision boundaries apart to leave fewer regions of ambiguity) [191], [192]. An ideal ML defensive strategy shall comprise countermeasures in the training, testing and inferring phase, as well as security and privacy of the dataset [193].

Additionally, since a wide circulation of data will be inevitable in ML applications, it would be important to consider the aspect of data security and privacy, such as authentication/authorization, regulatory requirements, rotation of keys/certificates, etc. Native software security models and the different ML sub-framework privacy policies need to be adequately understood to achieve uniform security across the system. This is particularly important since, in ML, multiple components are often stacked upon each other to build the end-to-end solution. Significant efforts shall be made to improve the robustness and security of ML, especially for the safety-sensitive wireless communication field, where minor errors may lead to disastrous consequences.

VI. CONCLUSION

We have seen that there is enough promise in the value of ML to dream of and experiment with, a future in which ML can be an inherent element of wireless communications. However, for adopting ML in 5G/B5G, it is needed to consider that ML cannot be applied everywhere, bearing in mind that the costliness, time, latency, and delay introduced from some ML techniques are far from some real-time applications. ML and 5G have a lot of room to improve together as a discipline, and until the major telecommunication industry fully trusts ML, the rate of development in the area will be significantly constrained by the need to be meticulous and not break the current systems. Because ML could add uncertainty and complication to any network, our passion must be tempered by extreme caution. It is important for future researchers to make a critical evaluation of the trade-off between increasing the accuracy of a wireless system using an ML-based approach and the interpretability of the model, especially for applications in which regulatory requirements come into play. Additionally, the explainability of any decision made by the ML algorithm needs to be emphasized, as these decisions must be timely, robust, and secure at the same time. Having said that, the demand is clear, and the goal is in fact simplicity. After all, it is all about going back to the fundamentals, and from a communications engineer point of view, the end goal should not be ML *per se*, but how to lever techniques, such as ML algorithms, to optimize and improve 5G networks. This is particularly true now, considering that ML is becoming a mandatory skill set for any professional field seeking to optimize complex real-world problems. It is interesting to see how ML technology will impact the definition of next-generation wireless network standards, proving the level of commitment of the wireless academic and industrial areas to ML. As a consequence, the question is no longer whether ML will be integrated into mobile and wireless communication systems, but rather when such integration will fully take place.

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