Recent Results of Machine Learning Inspired Wireless Communications

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***Abstract*—It is expected that in the future, main core technologies will be based on machine learning (ML) which is a subsection of artificial intelligence (AI). So called intelligence will be embedded into Many futuristic applications like Internet-of-things (IoT), mobile communications, autonomous vehicles by resorting to the AI or ML. Moreover, it is a recent trend to deploy ML technology to 5G wireless communications to address challenges in physical layer design, decision making, network management and resource management. Thus, in this survey, the recent advances in ML and related methods in relation to wireless communications are reviewed, which are classified as: ML in wireless system applications, ML for optimizing wireless communication systems and also application of ML in 5G. Moreover, application of ML in 5G explores the utilization of ML in 5G resource management and 5G transmission technologies. Finally, future directions of ML in wireless communication is discussed.**

***Index Terms*—Artificial intelligence, Machine learning, 5G, Wireless communication**

I. INTRODUCTION

Wireless communication has drastically evolved in the past decades. In the beginning it only meant for pure voice transmission. However, today it transfers rich multimedia content and data. Along with that, increase of cloud computing and smart phone usage creates a huge amount of data traffic in wireless communication networks. To compensate the data traffic demand, wireless networks are using several technologies such as spectrum reuse, dynamic spectrum access (DSA), multiple-input multiple-output (MIMO), orthogonal frequency-division multiplexing (OFDM) etc. Currently, fourth generation (4G) cellular network is globally adopted and provide all-IP broadband connection. It uses intelligence significantly in almost every aspect including DSA, MIMO, cognitive radio (CR), mobility management etc. By 2020, it is expected that the amount of IP data handled by wireless networks will be increased by a factor of 100 compared to 2010. Fifth generation (5G) cellular networks should be able to meet that demand [1]. Moreover, 5G is going to make a global change by connecting anything to anything by integrating new trends like Internet of things (IOT) and massive machine-type communications (mMTC). This will increase the complexity in handling of 5G networks. Therefore, the intelligence in the current (4G) network will be insufficient and it needs more concrete Intelligence to handle the future wireless networks.

In the beginning, ML has been seen as sub field of computer science and it was isolated from other sciences. Today the role of ML in other sciences is realized and it is deployed in many sciences including optimization and control, data mining, medical diagnosis, stochastic modeling and also in wireless communication.

In wireless communication, cognitive radio is the earliest candidate to adopt ML. A considerable work has been carried out to leverage ML in CR. A survey on AI techniques used in CR has been published [4], which summarizes the ML and other AI techniques and presents the state of the art. Apart from that, a very few survey articles related to ML in wireless communication have been done [2], [3] and [8]. An inclusive survey on application of deep learning (DL) in mobile and wireless networking has been published in [3], where a very descriptive explanation about DL is provided with various application of DL in wireless mobile and network system. In [2], authors present an overview on application of ML in wireless networks, which gives detailed overview on how ML is used in wireless networks such as resource management, networking, mobility management and localization. A comprehensive tutorial on artificial neural network (ANN) and its application in wireless communication has been published in [8], which summarizes ANN application in unnamed aerial vehicle (UAV), wireless virtual reality (VR), caching, computing etc.

Apart from this, there are more wireless communication technologies focused on ML such as massive MIMO, non-orthogonal multiple access (NOMA), IoT, mMTC, resource management, direct device-to-device (D2D) communication, and etc. However there is lack of work done to summarize the ML techniques used in these aspects of wireless communication. Moreover there is no overall survey has been carried out to summarize ML in various aspects of wireless communication.Therefore, the objective of this paper is to summarize ML techniques used in various field of wireless communication and also to provide potential future directions and recommendations.

The rest of the article is organized as follows: Section II gives an introduction to machine learning. In Section III, we describe ML in wireless system applications and services such as IoT, mobile blockchain and mobile crowdsensing. Subsequently, the Applications of ML for optimizing wireless

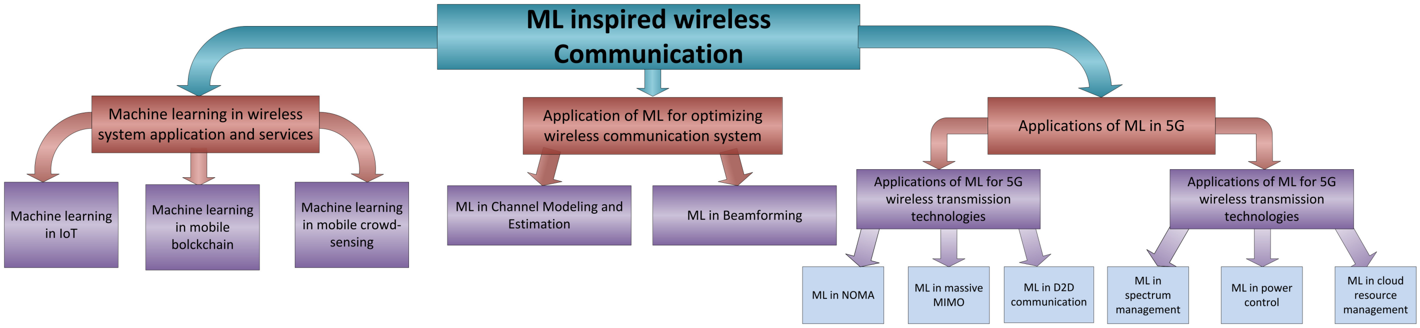

Fig. 1. Structure of the survey

communication systems are reviewed in Section IV. Then, we comprehensively highlight application of ML in various aspects of 5G in V. This section contains ML in 5G wireless transmission technologies and ML in 5G resource management. Finally, Section VI summarizes the survey by evaluating the scope for ML solutions in wireless communications and its potential limitations.

II. Machine Learning

Machine learning is an important component of AI which has currently dominated the AI field. Arthur Samuel described ML as: ”the field of study that gives computers the ability to learn without being explicitly programmed.” Main core technologies which are powered by AI mostly use ML to gain the intelligence. Similarly in wireless communication as well. Most of the existing and proposed AI solutions for wireless communication are based on ML. ML generally uses four important classes of learning process. Those are supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. There are several frame works have been suggested and developed in the past years to execute these learning procedures. Among those artificial neural network (ANN) is one of the most important frame work used in ML [8]. ANN’s learning pattern mimic the functional aspects of biological neural networks. Deep leaning (DL) is a sub field of ML which attracts the designers because of its ability to analyze critical problems, synthesize complex architectures, solving unfamiliar problems etc.

III. ML in Wireless System Application and Services

The journey towards smart city expects more innovative application and services from the available technologies. Therefore, Wireless system based applications and services are rapidly increasing from the recent past. There are several emerging applications and services which expect assistance from the future wireless communication systems. Applications Such as IoT, mobile crowdsensing and mobile block-chain can be seen as common examples. Most of these applications are related to massive number of edge devices Which creates tremendous amount of data. This huge volume of data should be managed efficiently to maintain the quality of service.

A. *ML in IoT*

IoT is a rapidly increasing technology due to the improvement in size and cost effective IoT enabled products. It is expected that the number of IoT enabled devices will reach 5 billion by 2020 [12]. These devices will create tremendous amount of data, where a huge computing power will be required to process these data it is impractical to accommodate that amount of computing power in a size and cost limited end devices. Therefore, ML is deployed to reduce the computational complexity, which will help to do the process by utilizing relatively less resources. Moreover, ML will be capable of extracting important patterns from the data and enabling self optimization, self organization and self-healing in the edge devices. In [12] authors propose an ANN framework which maps computational and communicational process, where data can be collaboratively processed by IoT nodes while data goes through the network. Therefore it reduces the latency of the overall process and also helps to protect the privacy of the information. IoT connects billions of devices through Internet to facilitate various kind of services. Most of the time many of these devices may cause potential risks in security and privacy. Since IoT creates a dynamic environment, deploying a fixed security protocol will be outdated within a short time period. Therefore the security solution should have intelligent embedded in it to evolve with the environment. Concerning that, authors in [13] focus on ML based security techniques for IoT systems. Moreover, they presents learning based access control, ML based secure offloading and malware detection methods to ensure the data privacy.

B. *ML in Mobile Block-chain*

Blockchain is a continuously updating digital list which publicly records every economic transaction. Embedding blockchain in mobile environment is still a challenging task since it requires high computing power and consume more energy, which are critical and limited resources in mobile devices. Mobile blockchain has many similarities with IoT. Therefore, most of the proposed ML based solutions which focus IoT also applicable in mobile blockchain. Apart from that, there are some specific challenges has to be solved in mobile blockchain application. Mobile block-chain requires more computing power, energy, and security compared to

IoT application. considering that, intelligent resource handling for edge computing service provider in mobile block-chain networks through deep learning is proposed in [14]. Which will reduce the computing complexity and power consumption required for the mining task. To overcome the security threats, ML and game theory based algorithm is used in [15], where the activities of the stakeholders are continuously monitored to protect the network from the major attacks.

C. ML in Mobile Crowdsensing

Mobile crowdsensing (MCS) is a technique of sensing huge amount of data through a large group of mobile devices which has the ability to sense various physical parameters. Sensed data is collectively shared to extract information of interest. In the same fashion like mobile block-chain, mobile crowdsensing also has many similarities with IoT. However, there are some unique challenges has to be overcome in mobile crowdsensing due to the potential limitations of the mobile devices and services, which involves bandwidth, energy and computational power. ML can be deployed to intelligently utilize the resources, empower security and increase the quality of service (QoS). Considering that, In [16], deep reinforcement learning is used to identify the best cell for obtaining the sensed data in sparse mobile crowd-sensing, which will reduce the amount of data to be sensed while maintaining the same quality. Additionally, mobile crowdsensing face more security threats while sensing and exchanging information. Concerning that, in [17], authors discuss the security threats in mobile crowdsensing and propose deep learning based security technique to empower the security strength of the system. Moreover, to increase the QoS of MCS, Multi-agent Reinforcement Learning is used in [18], which helps to learn optimal sensing policies and increase users payoffs.

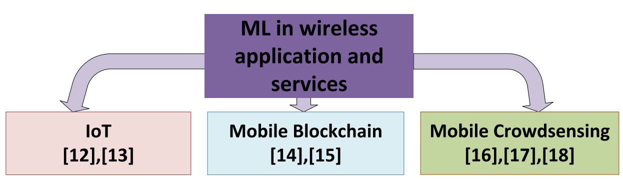

Fig. 2. ML in wireless system application and services

IV. Applications of ML for Optimizing Wireless Communication Systems

A. ML in Channel Modeling and Estimation

An interest has been developed toward geometrical channel modeling because of its large range of applications in wireless communication. In geometrical channel modeling, the transmitter, the receiver and the scatterers are considered to be located withing a specified geometry and scatterers are assumed to be distributed according to the certain statistical distribution. Figure 3 shows spheroid geometry with the transmitter and the receiver at its focal points where, the scatterers are assumed to be randomly distributed inside the geometry. In [19] a novel cluster-based geometrical stochastic MIMO channel model has been proposed. This dynamic scattering channel model based on a ML clustering algorithm and the closed form expressions for marginal probability density function (PDF) of (Angle of Arrival) AoA have been obtained. Moreover, the space-time cross correlation for different clusters have been obtained and it have been shown that, cross correlation increases with the angle range of the cluster.

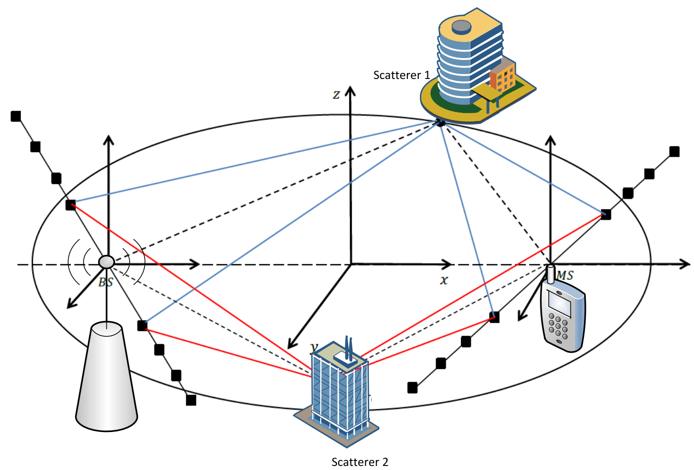

Fig. 3. Spheroid geometry, in which the transmitter and the receiver located at focal points and the scatterers are distributed within

In wireless and signal processing systems, channel estimation is a vital component. In [20] authors proposed approach to building a channel estimators based on approximated regression using artificial neural network models. Results presented in [20] shows that, the learned estimator can provide varies channel conditions.

B. ML in Beamforming

Beamforming improves the signal-to-interference-plus-noise ratio (SINR) at the intended users and reduces the interference to other users by improving the directionality of the transmit signal. The beamforming is performed by multiplying the transmit signals by beamforming coefficients, which are calculated according to the channel status. Highly mobile environment causes rapid changes in the channel and requires frequent computation of beamforming coefficients which will increase the computational complexity. Machine learning can be incorporated in such system to improve the efficiency of the beamforming calculation and reduce the computational complexity. Beamforming for a general antenna array system is considered in [21] and two layer neural network is deployed in to the system to improve the overall efficiency. When we consider a mmWave system, channel state will vary more frequently as the mmWave is vulnerable to atmosphere and other environmental parameters. Considering these characteristics, in [22], deep learning based algorithm is proposed to determine the beamforming coefficient for highly mobile mmWave system.

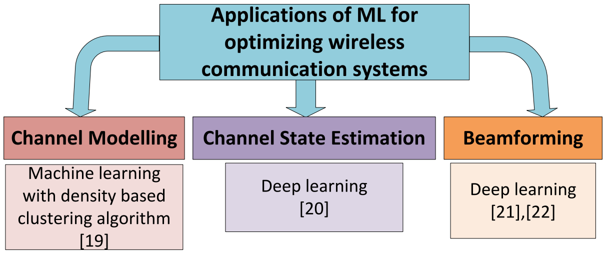

Fig. 4. ML in optimizing wireless communication systems

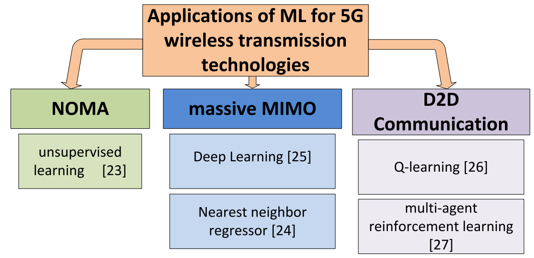

Fig. 5. ML in 5G wireless transmission technologies

V. Applications of ML in 5G

A. Applications of ML for 5G wireless transmission technologies

1) ML in NOMA: Recent past non-orthogonal multiple access (NOMA) has been introduced as a technique to improve the spectral efficiency. In [23] Cui et al have investigated the sum rate maximization problem of mm Wave NOMA systems. By assuming poison cluster process for users' locations of different clusters, ML based user clustering algorithm have been developed. The results presented in [23] have shown that the performance of the mmWave NOMA systems higher than the conventional systems. Moreover, it has reveled that K means provide an effective framework for user clustering in mmWave -NOMA systems.

2) ML in Massive MIMO: Massive multiple input multiple output (massive MIMO) systems are using multiple antenna elements, which have different configurations. Massive MIMO systems have advantages such as high capacity improvement, better data rates, improved link reliability and coverage over the SISO systems. Traditional MIMO systems lack of optimal performances due to the use of rigid analytical encoding and decoding schemes. In [24] authors propose a novel approach to estimate the multipath signal parameters in wireless communication systems by adopting the nearest neighbor regressors as ML algorithm. The proposed method is able to determine the positions of mobile stations as well as minimize the measurement noise. In the literature several MIMO detection methods have been proposed. Binary detection and Maximum likelihood detection have the drawback of computational complexity resulting impractical for several applications. Suboptimal detection algorithms based detectors as well as advanced detectors have been introduced lately. Aforementioned advanced detectors are based on algorithms such as decision feedback equalization, approximate massage passing and semidefinite relaxation [25]. In [25] Samuel et al has been proposed a general framework based on deep neural network for MIMO detection. The proposed framework accurately detects over channels with different characteristics.

3) ML in D2D Communication: Device-to-device (D2D) communication is an important component for the future (5G) wireless communication system as it decreases backhaul and fronthaul loads by enabling a direct communication between the devices. And also it helps to utilize the allocated spectrum more efficiently. Although it has many advantages, it requires more complex control mechanism to reduce interference produced by D2D users in order to maintain the performance of the overall system. ML techniques can be deployed to reduce the interference by intelligently sharing the resource blocks and controlling the transmission power in an adaptive manner. In [26], cooperative reinforcement learning based adoptive power allocation technique is proposed to reduce the interference in a D2D communication system. Content caching also a challenging task in D2D communication due to dynamic and sporadic movement of the devices. To overcome this challenge multi-agent reinforcement learning (MARL) based algorithm is proposed in [27]. Although D2D communication reduce the overall burden of the base station (BS) still Power allocation for D2D links are controlled by the BS. Therefore it remains as a burden to BS. As a solution for this, deep neural network (DNN) based completely distributed power allocation technique is proposed in [27], where D2D transmitter can decide the transmit power independently. To achieve this, devices are trained as a group using DNN and act independently, which reduces the burden of the BS.

B. Applications of ML for 5G resource management

In wireless communication, utilization of the resource is always a challenge due to limited and expensive resources and huge data traffic. Moreover in 5G, data traffic will be increased by a tremendous amount where a deployment of highly effective and dynamic resource management technique will be required. It can be achieved by embedding ML in to resource management task. In the following we will elaborate ML inspired management of spectrum resource, energy resource and cloud resource.

1) ML in Spectrum Management: Frequency spectrum is the most valuable and limited resource among wireless communication resources. Moreover effect of interference make spectrum utilization a complex task. Various ML techniques are proposed to compensate the huge traffic demands and efficiently manage spectrum resources. In [29], noncooperative game and reinforcement learning based algorithm is used to enable dynamic spectrum access which maximize the overall throughput in a millimeter-wave ultradense networks. Moreover Other ML techniques such as combined neural network [30], reinforcement learning [31], deep neural network [32] and deep reinforcement learning [33] are proposed to exploit the available frequency spectrum. Additionally, genetic algorithm [34] and Artificial immune system (AIS) [28] based approach is also used to solve the dynamic channel-assignment problem.

2) ML in Power Control: In wireless communication, available frequency spectrum is reused to achieve high data rate requirement. And also reused spectrum is shared between multiple users simultaneously to increase exploitation of the used spectrum. Both spectrum reuse and spectrum sharing will cause inter-user interference and lead to errors unless signal power is under constraints. Effective control of the signal power can reduce inter-user interference, and it will increase system throughput. In the following ML techniques based power control methods are elaborated.

In [35], authors Presents a hybrid cognitive engine (CE) which combines random neural networks and genetic algorithm. The CE is capable of predicting optimal transmission power to reduce inter cell interference (ICI) by analyzing signal-to-interference, signal to noise ratio and an ICI of the successive time frames of the spectrum block. Moreover Q-learning [36], [37], reinforcement learning [38] and deep learning [39], [40] based power control techniques are used to reduce ICI.

3) ML in Cloud Resource Management: Cloud will be an essential resource for future wireless communication system where it enables various applications. Cloud based radio access networks (C-RAN) is one of it which enables the communication through huge number of remote radio heads (RRH).These are connected to a centralized baseband unit (BBU) pool which is in the cloud. In the concept of caching in UAVs to enable C-RAN through it, Authors in [41] propose echo state network (ESN) based caching which is aware of various information about the users. By analyzing user information through ESN frame, it predicts the UAV's optimal location and cache content to enhance quality of experience (QoE). Considering limited information about the state of the network and the user, authors in [42] propose ML framework of ESNs to determine the cache content of RRHs and BBUs. Moreover, reinforcement learning [43], supervised learning [44] and ML with Dynamic Investment Strategy with Accounting Rules (DISAR) System [45] based cloud resource management strategies are also used for various applications.

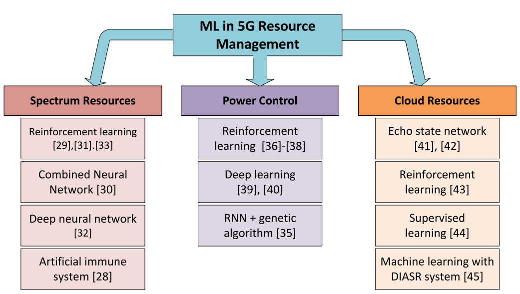

Fig. 6. ML in 5G resource management

VI. Related Projects

5G-PPP CgNet (Cognitive Network):"Building an intelligent System of insight and action for 5G network management" [46]. This is a project funded by EU Horizon 2020 and also co-funded by the European Commission under the ICT theme. which targets intelligent network management in 5G IoT scale. The goal of this project is to utilize machine learning techniques to achieve effective data acquisition, efficient resource allocation, accurate network scaling, highly sensitive fault recognition and more secure security protocol.

AI for Space Communications :This is a project funded by NASA John H. Glenn research centers space communications and navigation (SCaN) group [47]. The goal of this project is to utilize AI and machine learning to design more efficient space communication system. which also focus on creating cognitive radio applications which is capable to identify and adapt to space weather. Moreover, they have presented resource allocation algorithm for space communication using multiobjective reinforcement learning [48], Which minimizes the performance error of the system.

VII. Scope for ML Solutions in Wireless Communications

There are several works have been done to embed machine learning in wireless communication system. Most of the proposed techniques and solutions are focusing on a single application. Moreover, proposed applications use different learning frameworks to train the system. To work as a single system, all of the applications should be connected together. For this reason, it needs a common platform which integrates and control all the intelligent agents. Moreover, There are high chances that the machine learning techniques may give bad strategies in the beginning of the learning process. This happens due to lack of datasets to train the agent. As a solution for this, transfer learning can be embedded in the early stages of learning. Where it takes datasets from a different but related problem to train the agent in the stages of the learning process.

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