Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 10, October 2022

Machine Learning Applications in Wireless Communications

Rahul Vishnoi, Assistant Professor,
Department of Electrical and Communication Engineering, Teerthanker Mahaveer University, Moradabad, Uttar Pradesh, India
Email Id- ra_v@yahoo.com

ABSTRACT: This article examines a variety of Machine Learning (ML) applications in wireless communication technologies, with a particular emphasis on fifth-generation (5G) and millimeter wave (mmWave) technology. This article is a compilation of three studies on machine learning in wireless communication technologies. The paper discusses the need for machine learning to be integrated into wireless communication, the different types of machine learning techniques used in wireless communication, the benefits and potential of ML in wireless communication, and ML implementation parameters in wireless communication, as well as a study on RSS-Based Usage Classification in Indoor Millimeter-Wave Wireless Networks. Due to a broad range of service needs, varied features of industrial applications, and devices themselves, the next generation of wireless communication networks is becoming more complicated. Traditional networking methods, such as reactive, centrally controlled, one-size-fits-all solutions and traditional data processing tools, have limited capacity. In terms of operation and optimization, as well as cost-effective needs of networks and network providers, these methods do not support future sophisticated wireless networks. The rapidly growing demand for wireless communication technology necessitates research and development of new technologies and optimization methods.

KEYWORDS: Big Data, 5G, Millimeter Wave, Machine Learning, Reinforcement Learning.

1. INTRODUCTION

Machine learning (ML) is developing as one of the most promising technologies for assisting engineers in the conception and implementation of technologies such as driverless cars, industrial and home automation, virtual and augmented reality, e-health, and many other applications. The authors of paper lay out the factors that are driving the use of machine learning (ML) in wireless communication technologies, such as the need to move away from traditional optimization techniques and use Big Data to provide the best quality of service (QoS) to users while also managing the complexity of future networks. The authors of article set out the many machine learning models that are used to deploy new wireless communication technologies while also analyzing numerous publications to give a comprehensive look at the usage of machine learning in optimization. They also go through some of the advantages and uses of machine learning in wireless communication technologies, with an emphasis on the fifth generation [1].

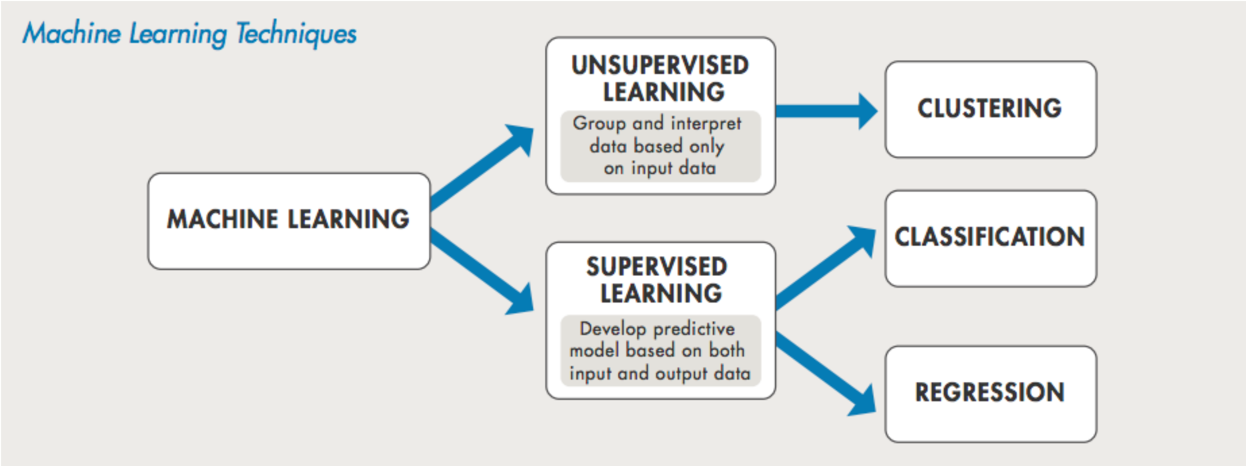

Figure 1: Classification of machine learning

We also discuss a use case of Machine learning-based optimization of Indoor Millimeter Wave [2]–[4] (mmWave) networks, as mmWave is a technology that aims to free up congested bandwidth at the ultra-high frequency range of 300 MHz to 3 GHz, and is also an integral part of 5G in providing data speeds of up to 100 Gb/s. The article examines the need for machine learning in wireless communication technologies, as well as the reasons that drive it. The conventional and prevalent method entails the optimization of a single key performance indicator on its own (KPI). This implies that the engineers are analyzing and optimizing the network using a restricted collection of data specific to the network. The value added by Data Analytics [5] to optimization is only useful when the variety of data sources is extended and a user-centric, quality of experience (QoE) approach is used to improve end-to-end network performance and efficiency, according to the study [6]. ML is being implemented by network operators and designers for a variety of reasons. The variables are divided into three groups in the paper: cost and service, use, and technological drives. Users' demand is growing at an exponential pace, but they are not increasing their wireless payments, necessitating the urgent requirement for cost-effective optimization methods. According to the study, network operators must manage traffic based on QoS, increase efficiency in order to retain customers while keeping a steady profit margin, and improve network performance and QoE [7].

2. DISCUSSION

To offer virtualized services like mobile edge computing more effectively, the next generation of wireless networks will need a strong analytics framework as illustrated in figure 1.

2.1. Supervised learning

In supervised learning, the programmer feeds sample data with a known result to the model. Each Sample value corresponds to a single result. The aim is to feed Sample inputs together with known outputs into the model, then use the trained model to predict fresh sample outputs. This kind of ML Model is useful for applications that need to train their algorithms on a huge quantity of data. To deal with rising traffic demands, this kind of machine learning is utilized while installing 5G, LTE tiny cells. These systems collect radio performance data from cells, such as path-loss and throughput for certain frequencies and bandwidth settings, then modify the parameters using ML-based algorithms to anticipate how a user would perform. This kind of machine learning is used to build route loss prediction models, infer unobservable channel state information, model and estimate objective functions for link budget and propagation loss for next-generation wireless networks, and other applications [1].

2.2. Unsupervised learning

The data used to train the model is an unlabeled collection of various attributes, and the system tries to find subgroups with similar characteristics among the variables without the need for human interaction. When it comes to grouping edge computing devices in a network, algorithms like K-means clustering and generative deep neural networks come in handy. This type of machine learning, according to the authors of the paper is useful for anomaly and fault detection, storing data in clusters in data centers to reduce unnecessary data travel among distributed storage systems, reducing latency by clustering fog nodes to automatically decide which low power node needs to be upgraded to a high power node, and data-driven resource management for ultra-dense small cell network [8].

2.3. Learning through Reinforcement

Wireless networks function in a probabilistic environment at all times. The authors of the article propose that the system characteristics and dynamics be modeled using a markov decision process (MDP) to achieve the network's most efficient and optimal operation. A network environment interacts with a reinforcement learning (RL) model, which makes choices at regular intervals. In every decision point accessible at the current states, the model must select an action a, to which the system must assign a positive or negative score R(s,a), and then proceed to a new state. The state transition probablity Pst (s,a) is independent of all prior states and actions, according to the markov property. Because we need to optimize this decision-making process, the RL model must keep track of all prior probabilities and their outcomes in order to assist us in choosing the best choice at each given decision point. The optimal choice at any moment is denoted by the reference. V denotes the value return at any arbitrary decision point. As a result, the study argues that if the MDP is known, the RL model can predict the best feasible outcome value V [9].

This technique may also be employed if the MDP is unknown, in which case the RL model will learn via trial and error. We can see how RL may be utilized for admission control, load balancing, mobility management, resource management, and dynamic channel selection (DSA) because of its flexibility to changes in the environment. The authors of emphasize the use of Q-learning based techniques for optimizing cell range extension (CRE) bias values for each device, as well as QoE-based handover decision for HetNets, user scheduling in small cells for energy harvest, proactive resource allocation in LTE-U networks, and Jamming resilient control channel in CRNs.

5G [10] intends to boost data speeds from 1 gigabit per second in 4G to 20 gigabits per second in 5G to accommodate high-demand applications. This is accomplished by using large quantities of spectrum resources in the mm and cm wave bands. Massive multiple input multiple output (MIMO) will be used in 5G to improve spectral efficiency. By utilizing deep neural networks for channel estimate and direction of arrival, machine learning will help to improve MIMO. According to the article ML aids in the categorization of channel state information (CSI) in order to choose the best antenna indices. Small base stations (SBS) are clustered using machine learning to allow for greater spectrum resource utilization, resulting in higher bandwidth per user. It's also used to relieve backhaul connection congestion by identifying and storing the most popular items at the network edge. RL is used to minimize the negative effects of spectrum sharing on PAL nodes and to get opportunistic access to the spectrum in order to improve dynamic spectral access.

By offering enormous bandwidth and fast data rates, mmWave plays a key role in bringing 5G to consumers. As previously stated, 5G necessitates the deployment of SBSs to assist relieve network stress. This allows mmWave to be utilized as a transmission medium since 5G can take use of the 60GHz bandwidth and short-range propagation characteristics. This makes network densification easier.

User-induced channel effects vary considerably with user activity and equipment utilized, according to the reference, and are particularly evident at mmWave frequencies. According to the authors of article networks must develop to use network radio resource management (RMM) optimisation methods based on detecting user use cases as well as user channel induced impacts. According to the study, the usage of wearable sensors is often observed in literature, which aids in the recognition of common UE and use cases. In terms of the orientation angle relative to the direct geometric route to the access point, the authors describe three typical use scenarios and assess the received signal strength (RSS) for Line of Sight (LOS), Quasi of Line of Sight (QLOS), and Non Line of Sight (NLOS) parameters (AP). The authors eliminate route loss and large scale fading in the preparation of data by applying a low pass filter to raw RSS data to recover small scale fading for analysis. The authors developed the k-means method to determine if the first UE use case is static or in motion. The number of clusters was fixed to two, and the algorithm was given the variance of small scale fading as input.

The writers were able to anticipate the user's condition with a 99.8% accuracy. Although the mistake is more prevalent in the non-static use scenario, the authors think it is inevitable. Using the K-Means findings, a low pass filter with the proper critical frequency is then applied to the RSS segment. As a result, a vector Sn represents the equivalent small scale fading.

$$[s1, s2, sn] = Sn \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

The n-th segment's small-scale fading is represented by sn in equation 1.

The authors were able to extract six statistical characteristics after obtaining small scale fading, which they subsequently analyzed. Variance, Rice Factor, Nakagami Parameter, Channel Coherence Time, AFD, and LCR were the six characteristics. Because the range of each characteristic varied greatly, the authors scaled the values before feeding them into the classifier. The authors conducted a 10-fold cross validation.

CONCLUSION

We must keep in mind that data will play a large role in next-generation networks. As a result, advanced machine learning must be used by network operators for effective operation, control, and optimization. Even while network operators are still unsure about incorporating ML into their networks, it is obvious that it will play an essential role in the implementation of 5G. Paper demonstrates the potential of ML by categorizing the UE use case, which may aid in data congestion prediction, QoS and QoE optimization. However, because of the complexity, expense, and delay imposed by machine learning, it cannot be used everywhere. As a result, future researchers must carefully evaluate the trade-offs between improving the accuracy of a wireless system by using ML-based algorithms and the model's interpretability and disadvantages.

REFERENCES:

[1] C. Jiang, H. Zhang, Y. Ren, Z. Han, K. C. Chen, and L. Hanzo, “Machine Learning Paradigms for Next-Generation Wireless Networks,” *IEEE Wirel. Commun.*, 2017, doi: 10.1109/MWC.2016.1500356WC.

[2] B. Ai *et al.*, “On Indoor Millimeter Wave Massive MIMO Channels: Measurement and Simulation,” *IEEE J. Sel. Areas Commun.*, 2017, doi: 10.1109/JSAC.2017.2698780.

[3] S. H. Min *et al.*, "Spatial and temporal characterization of indoor millimeter wave propagation at 24 GHz," *Int. J. Antennas Propag.*, 2016, doi: 10.1155/2016/2318731.

[4] E. Torkildson, U. Madhow, and M. Rodwell, "Indoor millimeter wave MIMO: Feasibility and performance," *IEEE Trans. Wirel. Commun.*, 2011, doi: 10.1109/TWC.2011.092911.101843.

[5] C. W. Tsai, C. F. Lai, H. C. Chao, and A. V. Vasilakos, "Big data analytics: a survey," *J. Big Data*, 2015, doi: 10.1186/s40537-015-0030-3.

[6] "WILEY-VCH," *Pharm. Unserer Zeit*, 1997, doi: 10.1002/pauz.19970260615.

[7] S. Bayat, Y. Li, L. Song, and Z. Han, "Matching Theory: Applications in wireless communications," *IEEE Signal Process. Mag.*, 2016, doi: 10.1109/MSP.2016.2598848.

[8] "China Communications," *China Commun.*, 2017, doi: 10.1109/cc.2017.8107626.

[9] X. Wang and E. Serpedin, "An Overview on the Applications of Matrix Theory in Wireless Communications and Signal Processing," *Algorithms*. 2016. doi: 10.3390/a9040068.

[10] M. S. Ansari and J. Ahmed, "Upcoming 5G Wireless Technology and its Security Concept of wireless technology, Architecture of 5G Requirements of 5G, Security of 5G," *Int. J. Adv. Res. Comput. Sci.*, 2017.