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Machine Learning Approaches for 5g Network Challenges

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Abstract: *The rapid development of 5G networks has brought many new challenges, networking becomes more complex, the services are more diverse, and the connections are increasing on a large scale. In this paper a comprehensive analysis is carried out to find the suitability of machine learning approaches for addressing various 5G network challenges such as data rate, beam selection, reducing latency, energy efficiency to mention a few. A brief introduction to 5G networks and an overview of Machine learning approaches are presented. A detailed and comprehensive survey of machine learning (ML) techniques and ML inspired approached to handle 5G network challenges are presented and ML proves to be a promising solution for a variety of issues faced in 5G networks and beyond.*

Keyword: *5G, ML, Supervised learning, Reinforced learning, Unsupervised learning, ANN, HMM, SMO*

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I. INTRODUCTION:

Integration of new technologies such as massive MIMO, full duplex (FD) wireless communication, mobile edge computing (MEC), and network slicing (NS) in 5G is introducing several challenges. Using traditional ways of network operation and maintenance will make meeting new requirements for network development difficult. 5G technology is expected to support three general types of services: enhanced Mobile Broadband (eMBB), massive Machine-Type Communications (mMTC) and ultra-reliable and low-latency communications (URLLC) based on different QoS requirements. massive Machine-Type Communications (mMTC) provides scalable connectivity solutions for the massive number of devices using Multi-access edge computing (MEC) as a technology solution. These emerging technologies pose a wide number of challenges that need to be addressed. Some of the important challenges faced by 5G networks are listed as i) the management of large data volume caused by the UDSC (Ultra Dense deployment of Small Cells) ii) choice of Radio Access Technology (RAT) iii) massive MIMO challenges iv) interference issues iv) control and data plane separation v) intelligent authentication vi) beam selection vii) latency reduction etcetera. The 5G network challenges listed are to be addressed in order to meet the 5G requirements, hence the need to automate the network orchestration and management arises. To provide more intelligence in the management of 5G networks, efficient approaches that can effectively handle the large volume of data generated and other network resources must be deployed. Machine Learning (ML) has emerged as one of the most promising technique to handle the 5G network challenges. ML approaches have the potential to learn the system automatically, optimize and analyze large volume of data and predict the future scenarios. Thus, in this paper a comprehensive survey is carried out to find the feasibility of using ML approaches to handle various 5G network challenges.

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II. MACHINE LEARNING: AN OVERVIEW

Machine Learning enables applications and systems to learn automatically, predict and decide without human intervention and thus making machines intelligent. ML learns either from the available set of data or by interactions with the surrounding environments. Based on the learning mechanisms, the Machine Learning approaches are broadly classified as: (i) Supervised learning (ii) unsupervised learning and (iii) reinforcement learning [1,2,11]. In supervised learning, algorithm learns with the help of a training data set and uses this knowledge to label the output. Whereas, Unsupervised learning is not dependent on training data set. In this approach, the unlabelled heterogeneous data is divided into smaller homogeneous sub-sets which can be easily understood and managed. Semi-supervised learning technique, uses both the labelled and unlabelled data for learning. In reinforcement learning (RL) approach, the machine interacts with its environment to learn and aims at maximizing the reward. Thus, based on the challenges faced and the application, suitable ML algorithm is to be identified for deployment.

III. ML TECHNIQUES FOR 5G NETWORKS: A SURVEY

ML is being used for 5G network orchestration and management. Using ML for solving various 5G network related issues such as RAN congestion problem, flexibility, determining granularity, beam selection is reported in literature. A comprehensive analysis is carried out to understand the potential benefits of ML for 5G networks.

T.Koshimizu et.al [3], in their research employed soft margin-based SVM-ML with Gaussian Radial Basis Kernel function to determine the granularity of clusters in VANETs (Vehicular Adhoc Networks). The cluster size and span are determined with fewer training data sets and a better prediction accuracy is achieved.

Sharma S.K. et.al, [4] in their paper focused on RAN congestion problem and emerging Machine Learning (ML)-based solutions. The heterogeneity of the devices and the resource constrained mMTC environment are the key challenges in making ML approaches realizable. Authors have analysed the wide range of ML techniques and have proposed a low complexity Q-learning technique as a solution.

A. Yazar and H. Arslan [5], have proposed a novel machine learning (ML) based selection mechanism for the design of configurable waveform parameters from the flexibility perspective. Providing customized communication solutions for each user and service type is not possible without the flexibility in 5G and beyond. Different optimizations need to be done for the flexibility related structures of 5G and beyond systems.

B.Sliwa et.al [6] in their work attempted to improve the resource efficiency of car to cloud data transfer. ML based channel quality estimation is used for scheduling the transmission time of the sensor data. The average data rate is increased by up to 194% and the mean uplink power consumption is reduced by up to 54%.

Siddhant Ray and Budhaditya Bhattacharyya [7] used Hidden Markov Model (HMM) to learn network parameters and select the best eNodeB for cell association. Using the proposed HMM model for cell association, the authors have achieved ultra-low latency.

Arash Asadi et. al [8] proposed to use ML for beam selection at mmWave base stations. Fast machine learning (FML) proposed by authors, a low-complexity and highly scalable algorithm is coupled with a practical protocol design to meet the requirements of 5G networks. FML enables mmWave base stations to autonomously learn from their surrounding environment. On an average, FML needs only 33 minutes to achieve near-optimal performance.

To provide reliable and optimal cell association, a hidden Markov model (HMM) based machine learning (ML) technique is proposed by Balapuwaduge and F. Y. Li [9]. n this paper to perform optimal cell association. Network-assisted decision-making capability is exploited to choose the most appropriate eNodeB. Authors demonstrate the supremacy of the HMM based Machine learning technique over a random cell selection scheme.

Dual connectivity (DC) technology is used to meet the network challenges posed by user-centric ultra-dense networks (UUDN). Y. Yang et.al [10] have proposed an iterative support vector machine (SVM) classifier to select the codewords of Base Stations. Authors used Sequential minimal optimization (SMO) algorithm used for training all link samples reduced the computational complexity.

As ultra-low latency is the key metric in developing 5G communication, a proper cell association scheme is now required to meet the load and traffic needs of the new network, as compared to the earlier cell association schemes which were based only on the Reference Signal Received Power (RSRP). The eNodeB with the highest RSRP may not always be optimal for cell association to provide the lowest latency. This paper proposes an unsupervised machine learning algorithm, namely Hidden Markov Model (HMM) learning on the network's telemetry data, which is used to learn network parameters and select the best eNodeB for cell association, with the objective of ultimate ultra- low latency. The proposed model uses an HMM learning followed by decoding for selecting the optimal cell for association As ultra-low latency is the key metric in developing 5G communication, a proper cell association scheme is now required to meet the load and traffic needs of the new network, as compared to the earlier cell association schemes which were based only on the Reference Signal Received Power (RSRP). The eNodeB with the highest RSRP may not always be optimal for cell association to provide the lowest latency. This paper proposes an unsupervised machine learning algorithm, namely Hidden Markov Model (HMM) learning on the network's telemetry data, which is used to learn network parameters and select the best eNodeB for cell association, with the objective of ultimate ultra- low latency. The proposed model uses an HMM learning followed by decoding for selecting the optimal cell for association

The volume of training data and authentication problem dictates the choice of learning algorithm in intelligent authentication schemes. H. Fang et.al [12] have presented ML paradigms for intelligent authentication and shown that reliable, situation-aware device validation can be carried out even under unknown network conditions and unpredictable dynamics.

Xinyu Gao et.al [13] used Adaptive Cross Entropy (ACE)-based hybrid precoding scheme for a new energy-efficient hybrid precoding architecture proposed by them. The probability distributions of the elements in hybrid precoder are adaptively updated by minimizing the Cross Entropy. Results obtained by authors show that near-optimal sum-rate performance and higher energy efficiency is achieved by the proposed scheme. Table 1 summarises the various ML solutions used to address the existing challenges in 5G networks.

Table1: Summary of ML techniques used to address the challenges in 5G Networks

Ref No	5G Network challenge addressed	ML Solution Proposed	Objective	Inference
T.Koshimizu et.al [3]	Prediction and Decision Making	SVM	To determine the granularity	ML prediction performance achieved satisfactory results with fewer training data.
Sharma S.K. et.al, [4]	RAN congestion problem	Q Learning	To address the problem of RACH congestion in cellular IoT networks	Proposed Low-complexity Q-learning approach enhances learning performance and convergence
A. Yazar and H. Arslan, [5]	Flexibility	Novel ML	To control overheads in systems using multi-numerology structures	A new flexibility metric is developed
B.Sliwa et al., [6]	Resource Efficiency	M5 Decision Tree (M5T) and Linear Regression (LR))	To improve the resource-efficiency of car-to-cloud data transfer.	Higher data rate is achieved with reduced mean uplink power consumption.
Siddhant Ray and Budhaditya Bhattacharyya [7]	ultimate ultralow latency	Hidden Markov Model (HMM)	To select the best eNodeB for cell association and achieve ultimate ultralow latency	Ultralow latency is achieved by using HMM learning
Arash Asadi et. al [8]	Beam Selection	Fast Machine Learning (FML)	To use ML for beam selection at mmWave base stations	Proposed FML requires on average only 33 minutes to achieve near-optimal performance.
I. A. M. Balapuwaduge and F. Y. Li [9]	Networks resource management	Hidden Markov Model (HMM)	To perform optimal cell association in mMTC networks.	Optimal cell association in mMTC networks is achieved
Y. Yang et.al [10]	Decision making	Iterative SVM	To select the codewords of Base Stations	Lower computational complexity is achieved using the iterative SVM-SMO algorithm
H. Fang et.al [12]	Intelligent Authentication	ML	To use ML for intelligent authentication	Performs well even under unknown network conditions and unpredictable dynamics
Xinyu Gao et.al [13]	Energy Efficiency	Adaptive Cross Entropy optimisation	To adaptively update the probability distributions of the elements in hybrid precoder	Near-optimal sum-rate performance and higher energy efficiency is achieved.

IV. CONCLUSION:

This paper presents a comprehensive survey of various ML tools and algorithms with respect to 5G networks and challenges faced. ML proves to be a powerful tool to improve the performance of 5G networks with respect to congestion reduction higher data rates, low latency, high energy efficiency, better beam selection etc., The future is going to be “5G and beyond” and the performance of future networks depends largely on automatic, intelligent systems. Situation-aware adaptive learning and collaborative learning could be exploited to enhance the performance of the ML techniques for future networks.

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