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Artificial Intelligence Driven Massive MIMO for Better Energy Efficiency in Wireless Communication Systems.

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Abstract:

Data traffic on mobile networks is rapidly expanding, putting operators under pressure to investigate various methods for capacity increase. As a result, the development and maintenance of contemporary 5G networks has become more difficult. Because of this, new methods to network design and administration are required that enable self-organization capabilities. We provide a new intelligent approach for large MIMO beam forming performance optimization in this work. Deep adversarial reinforcement learning is implemented in the proposed approach by combining three neural networks in a cooperative fashion. Neural networks trained to create realistic user mobility patterns are then employed by a second neural network to build antenna diagrams suitable for that user. Both of these networks get a proportional reward from a third neural network, which assesses the effectiveness of the created antenna design. The suggested technique has the benefit of being self-learning and not need extensive training datasets.

Keywords: AI, MIMO, machine learning, Capacity, NN.

1. INTRODUCTION

There has been considerable increase in wireless network data consumption over the past several years, spurred on by the introduction of new services with high QoE (Quality of Experience) standards. According to Cisco's Visual Index, report wireless and mobile devices will produce more than 63% of global Internet traffic by 2021[1]. Artificial intelligence will have an essential role in managing big data as advanced data analytics and organizing various communication devices in the future of mobile or wireless networks. In short, Xhang et al. [2] stated that the mobile intelligence system should be self-adaptive, self-aware, proactive, and prescriptive. On the other hand, The infrastructure of mobile communication needs to be adaptive to diversified services and efficient and reliable, such as improving the performance of mobile broadband, minimize the peak-to-average power ratio (PAPR) [3], improving orthogonal frequency division multiple access (OFDM) [5], improved link quality [4].
In the 5G mobile communication system, the challenges will be appeared because of the huge nodes and mobile devices with fast data interchange and communication [5]. It was explained by Kibria et al. [6], who have overviewed data analytics, Machine learning, and AI in network communication. It supposed that the network management was and would be more complex within the new mobile communication generation network. Banupriya et al. [7] forecast that the traffic will rise to 1000 times in 5G mobile communication according to mobile end-user data speed and growth. Hence, traditional network management and techniques are not supported in the next generation of mobile communication [8].

2.AI Approach and Application in Mobile Communication

There are some classic artificial intelligence approaches, such as fuzzy logic and neural network. Then, the neural network would be extended to be better performance techniques such as machine learning and deep learning approaches. The basic approach is Fuzzy logic, which is processed any values and resulting in true and false. Another term in AI is reinforcement learning, a technique to design a computer or machine for learning by itself instead of being precisely programmed [12]. One of the techniques is Neural networks(NN). This technique can be made by a machine or computer able to self-learning to solve a problem. NN process adopts the brain human system and behavior. In the current issues, also deep learning (DL) has been
popular as an improved machine learning (ML). ML and DL are interesting approaches for advanced network traffic and management of future mobile communication. The two types of AI learning have been used in mobile communication: supervised learning and unsupervised learning.

Mobile Communications Technology	**Applied AI**
Autonomous vehicles and medical assistance devices	Automation with inherent artificial intelligence (AI) [9] Current and major algorithms in the specific field of artificial intelligence for autonomous vehicles. Such systems are particularly suited for high-level decision making since they must, by definition, be able to perceive and react to their environment in order to reach given objectives [10]
Internet of Intelligent Things	Artificial intelligence techniques employed to create such intelligence, and network solutions to exploit the benefits brought by this capability [11]
Mobile Cloud Computing MCC	Resource intensive applications such as augmented reality, artificial intelligence, artificial vision, object tracking, image processing, and natural language processing are becoming popular to manage MCC[12] .
5G Networks	AI and its subcategories like machine learning and deep learning have been evolving as a discipline, to the point that nowadays, this mechanism allows fifth-generation (5G) wireless networks to be predictive and proactive, which is essential in making the 5G vision conceivable [13].

Artificial intelligence (AI) has an essential role in increasing the mobile communication system's performance: proactive system, self-aware, self-adaptive, predictive, efficient, and cost-effective operation and optimization. This article describes several classic AI techniques and the current AI approaches in wireless communication. The techniques contained fuzzy logic, neural networks, reinforcement learning, and some AI techniques implemented on mobile communication. Some keys or terms challenges between AI and future mobile communication are how to manage such as big data, data analytics, higher frequency transmission, device-to-device communication, the reliable architecture, ultra-dense network, Massive MIMO, 3D Beam forming, V2X, Drone Base Station, Multi-Access Connectivity, mm-wave, Cloud-RAN, Edge Network, and Micro Base Station. The challenges are 5G generation issues and how the sixth generation (6G) of mobile networks will be driven to give stable networks and service types on huge mobile devices and data.

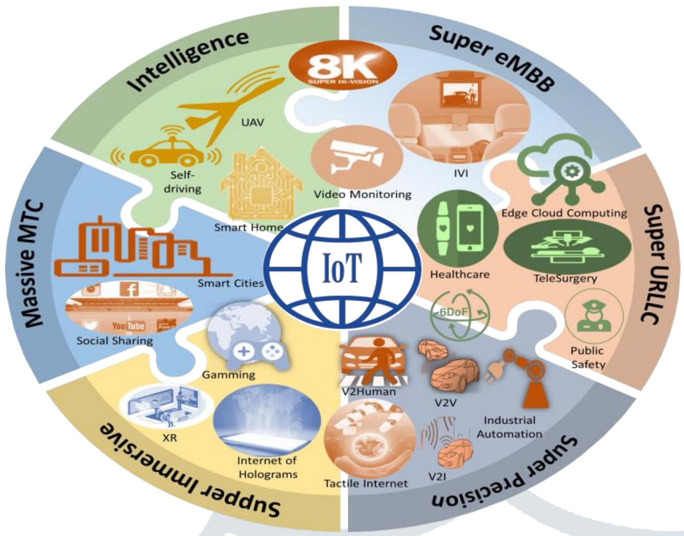

Fig1. The envisioned services and use-cases for Next generation wireless communication.

3.AI-powered Network Management

AI improves network management in different aspects in- cluding monitoring, processing, and decision-making. Ma- chine learning (ML) as a form of AI involves teaching the machines by making the data-driven decision (thinking) to per- form tasks and functionalities (acting) independently without human intervention. ML has great potential in supporting big data analytic, efficient parameter estimation, and interactive decision-making.

Subsequently, ML algorithms would make breakthroughs in the networking and communications fields, at both device and network levels, by enabling self-x networking (e.g. self- learning, self-reconfiguration, self-optimization, self-healing, self-organization, self-aggregation, and self-protection). For example, ML can be used to address the access congestion in IoE [3], intelligence to the PHY to empower smart estimation of parameters, interference mitigation, and resource manage- ment [4], DL for channel estimation and symbol detection [5],DL for dynamic radio resource allocation for V2V and V2X [6].

In the following, we will explain how ML algorithms including supervised learning, unsupervised learning, and rein-forcement learning, can be utilized in different network layers [9].

Supervised learning is a learning function that maps an input to an output based on the labeled training data, e.g. input-output pairs. There are many techniques developed under supervised learning that can be applied for network management including independent component analysis, locally linear embedding, principle component analysis, isometric mapping, K-means clustering, and hierarchical clustering. Such algorithms are applicable in wireless networks in different layers. In the physical layer, we may utilize the above techniques for channel equalization, channel decoding, predicting path-loss and shadowing, channel states estimation, beamforming, adaptive signal processing, etc. Supervised learning techniques are appli- cable in the network layer for caching, traffic classifica- tion, anomaly detection, throughput optimization, delay mitigation, etc.

Unsupervised learning is a type of self-organized learning that is used to discover undefined patterns in a dataset without pre-determining labels. Various techniques have been developed for unsupervised learning including k- nearest neighbors, neural networks, decision tree and random forest, Bayesian learning, linear / logic regression, support vector machine. In terms of network management, the above techniques can be used in network layer for routing, traffic control, parameter prediction, Resource allocations, RAT selection Handover and mobility management, Network slice selection and allocation, etc. In physical layer unsupervised learning can be used for channel-aware feature-extraction, optimal modulation, interference cancelation, Channel estimation, MIMO pre- coding, node association, beam switching, etc.

Reinforcement learning is about sequential decision- making, in which the agent ought to take actions in an environment with the goal of maximizing some notion of cumulative reward. Some of well-known techniques developed for network management are multi-arm bandit, temporal-difference learning, Markov decision process, SARSA learning, Q-learning, and Monte Carlo Method. These techniques can be applied in the application layer for proactive caching, data offloading, error prediction, and data rate allocation in network slicing. In the network layer, reinforcement learning can be used for multi-objective routing, packet scheduling, security, traffic prediction and classification, etc. While in physical layer, reinforcement-learning can be employed for link preservation, channel tracking, on-demand beam forming, energy harvesting, modulation selection, radio identification, etc.

4. AI BASED ALGORITHM FOR BASE STATION:

Mechanisms that employ artificial intelligence and machine learning to implement real-time changes to the network's architecture are crucial to its optimization and control. The network operational domain (RAN, transport, or compute) is used to further categories the solutions in this group.To better account for the capacity-limited wireless backhaul that connects the tiny cells (e.g., picocells, femtocells, unmanned aerial vehicles) to the core network, the learning approach proposed in can be further extended. In this setting, RL can be used to design unique end-to-end physical resource optimization algorithms that permit end-user devices to

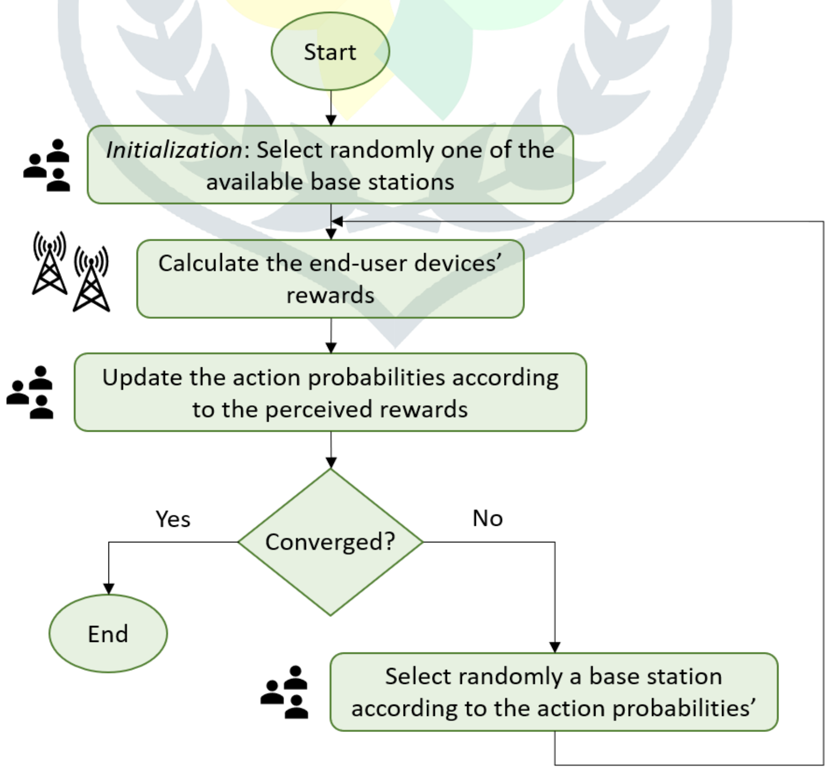

Fig2:Algorithm for base station

automatically adjust to the insecurities of the radio access and backhaul links.Mechanisms that employ artificial intelligence and machine learning to implement real-time changes to the network's architecture are crucial to its optimization and control. The network operational domain (RAN, transport, or compute) is used to further categorise the solutions in this group.

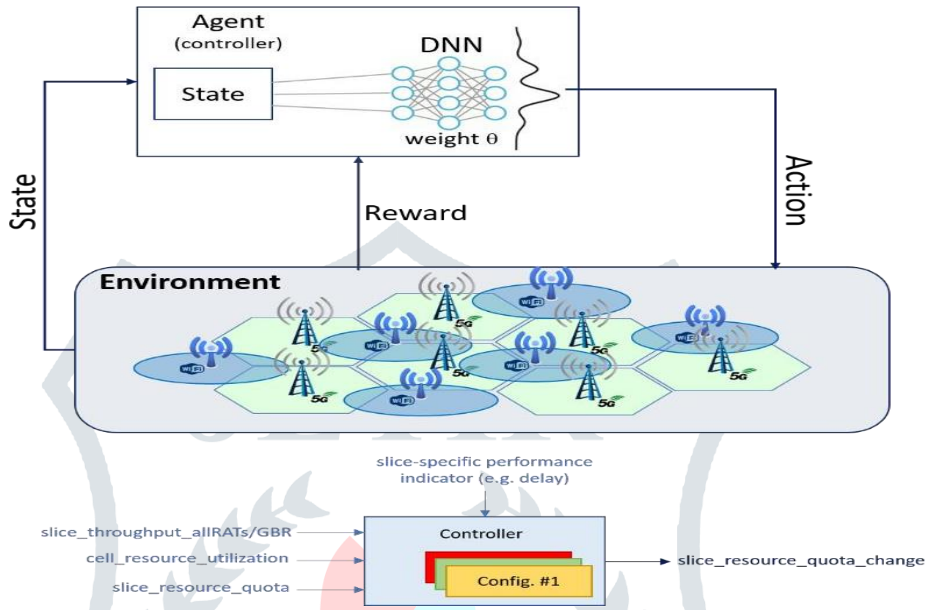

Fig3:Network Optimization and Control

5.RESULT ANALYSIS:

KPI	4G	5G & Beyond(Theoretical value)	5G(Estimated value)
Peak data rate	100Mbps	10Gbps=10^5Mbps	10Gbps approx
Latency	10ms	1ms	1ms
Maximum spectral efficiency	15bps/Hz	30bps/H	45bps/Hz
Architecture	MIMO	Massive MIMO	Massive MIMO
AI	No	Partial	Fully supported
Spectral Efficiency	1×	100×4G	100×4G
Switching	All packet	All packet	All packet
Mobility(Km/h)	200	300	350

Massive MIMO is expected to have a maximum data throughput of 10 Gbit/s, ten times that of current 4G at 1 Gbit/s. Under optimal conditions, Massive MIMO has the potential to achieve peak data throughput of 20 Gbit/s. Massive MIMO would provide a wide range of data speeds as perceived by the user. For wide regions of coverage, such as in urban and suburban areas, the user perceived data rate should be 100 Mbit/s, as opposed to 10 Mbit/s in current 4G systems. There are likely to be cases where the user-savvy data rate exceeds typical values (say, 1 Gbit/s inside), and these cases will occur in hot spots. Massive MIMO, the latest advancement in communication, is expected to achieve performance levels three times that of 4G in terms of spectrum efficiency. The potential efficiency increase compared to 4G may be greater in some circumstances than others (e.g., five times or higher in hot spots).

Scheme (No of Antennas,max 500)	Throughput(b/s)	Energy Efficiency(%)
MIMO	1.2	93%
m-MIMO	1.4	94%
AI/ML-mMIMO	1.6	98%

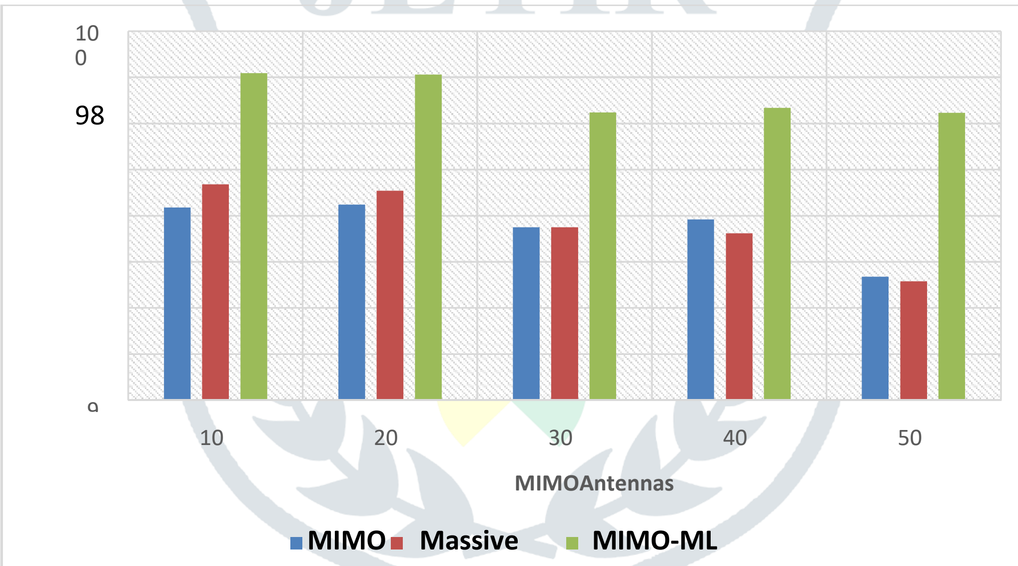

Fig4:Energy efficiency of AI/ML Massive MIMO.

5. CONCLUSION: Massive MIMO is expected to have a maximum data throughput of 10 Gbit/s, ten times that of current 4G at 1 Gbit/s. Under optimal conditions, Massive MIMO has the potential to achieve peak data throughput of 20 Gbit/s. Massive MIMO would provide a wide range of data speeds as perceived by the user. For wide regions of coverage, such as in urban and suburban areas, the user perceived data rate should be 100 Mbit/s, as opposed to 10 Mbit/s in current 4G systems.Here the energy efficiency of AI driven massive MIMO is 98% which is quite good for communication system.

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