Insightful 5G: Artificial Intelligence In Cellular Networks

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Abstract : 5G cell systems are thought to be the key empowering influence and framework supplier in the ICT business, by offering an assortment of administrations with various prerequisites. The institutionalization of 5G cell systems is being facilitated, which additionally infers a greater amount of the competitor advancements will be embraced. Along these lines, it is beneficial to give understanding into the competitor strategies all in all and look at the structure logic behind them. In this article, we attempt to feature a standout amongst the most crucial highlights among the progressive methods in the 5G time, i.e., there develops beginning knowledge in about each essential part of cell systems, including radio asset man-agement, portability the executives, benefit arrangement ing the board, etc. In any case, looked with ever - progressively entangled arrangement issues and blooming new administration prerequisites, it is as yet deficient for 5G cell systems in the event that it needs total AI functionalities. Subsequently, we further present essential ideas in AI and talk about the connection among AI and the applicant strategies in 5G cell systems. In particular, we feature the chances and difficulties to abuse AI to accomplish shrewd 5G organizes, and exhibit the viability of AI to oversee and arrange cell arrange assets. We imagine that AI-engaged 5G cell systems will make the acclaimed ICT empowering agent a reality.

***IndexTerms* - Component,formatting,style,styling,insert.**

I. INTRODUCTION

The fifth era portable system (5G) applies the up and coming age of versatile media transmission stan-dards which focuses at the requirements of 2020 and past. It goes for giving a total remote com-munication framework with assorted applications. Uniquely, 5G will be in charge of supporting three nonexclusive administrations, which are classi ed as improved versatile broadband (eMBB), enormous machine-type correspondences (mMTC) and ultra-dependable and low-idleness interchanges (URLLC) (likewise alluded to as mission-basic interchanges). These applications propose new execution criteria for dormancy, unwavering quality, association and limit thickness, framework otherworldly effectiveness, vitality proficiency and top through-put that should be tended to with the 5G innovation. To meet these criteria, continuous inquires about are led in numerous zones, principally centered around key innovations including gigantic different info various yield (MIMO), new radio access innovation (RAT), heterogeneous ultra-densification systems (UDN), channel coding and deciphering (for example polar codes) and mmWave get to [1]. Likewise, 5G systems will definitely be heterogeneous, with numerous modes and gadgets required through one brought together air interface custom-made for explicit applications. Thus, designs as the thick Het Net are included and 5G frameworks will be virtualized and actualized over cloud server farms. System cutting will be a noteworthy component of a 5G arrange, as will the utilization of another air interface intended to progressively streamline the distribution of system assets and use the range effectively. From the very beginning, 5G cellular networks were assumed to be the key enabler and infra-structure provider in the ICT industry, by offer-ing three types of services from enhanced mobile broadband (eMBB) with bandwidth-consuming and throughput-driving requirements to new ser-vices such as ultra-reliable low latency service (URLLC) and massive machine-type communica-tions (mMTC). In that regard, though technologies such as densified cells and massive multiple-input multiple-output (MIMO) are essential to boost capacity in the 5G era, it is cost-ineffective to deploy such techniques. Instead, 5G cellular net-works mainly revolutionize themselves by initially embracing the intelligence to agilely boost both spectrum efficiency (SE) and energy efficiency (EE). Specifically, 5G cellular networks provide alternative options for radio resource manage-ment (RRM), mobility management (MM), man-agement and orchestration (MANO), and service provisioning management (SPM) mechanisms. Hence, it is no longer necessary to build dedi-cated networks for individual services (e.g., the GSM-Railway communication networks). On the contrary, as depicted in Fig. 1, due to the devel-opment of smarter 5G networks, it will be feasible to provide customized end-to-end network slices (NS) [5] to simultaneously satisfy distinct service requirements, such as ultra-low latency in URLLC and ultra-high throughput in eMBB.

There is no doubt that 5G cellular networks will tailor the provisioning mechanisms for differ-ent predefined services and pave the way for the application of complete intelligence. However, it is still challenging and time-consuming for 5G cellular network operators to solve ever-increas-ingly complicated configuration issues and satisfy evolving service requirements, since 5G cellular networks merely possess more technical options

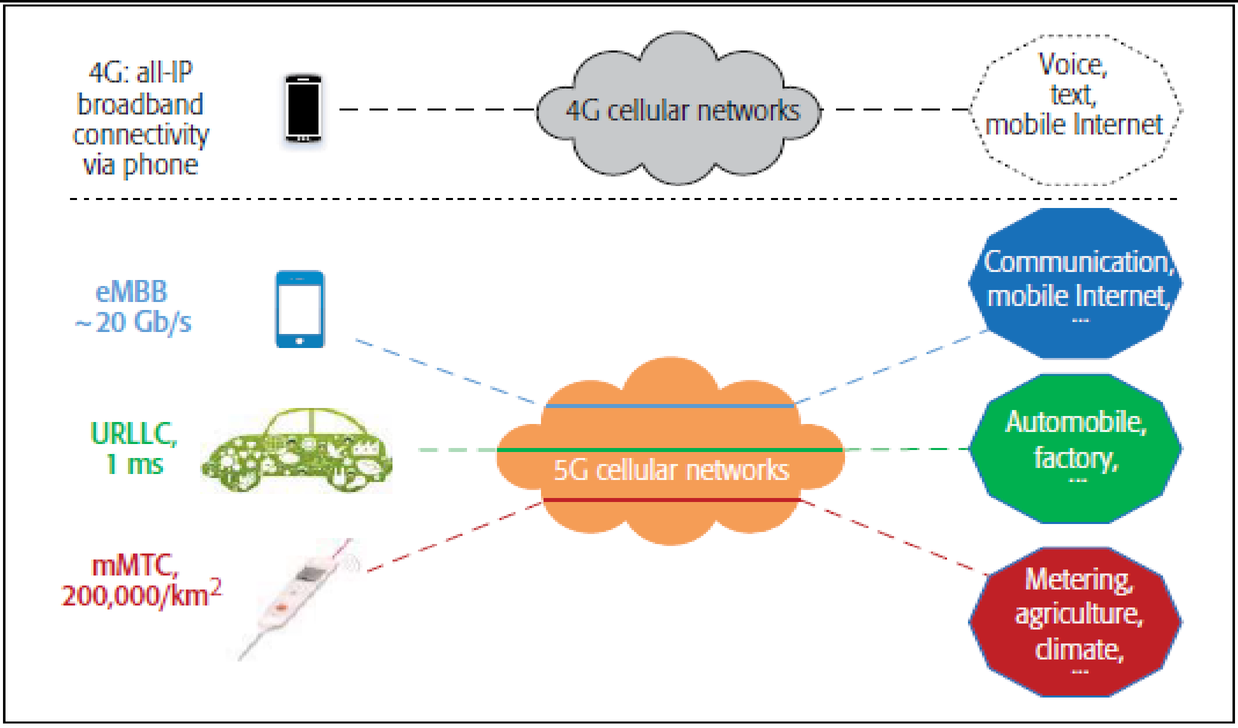

Fig.1 : 5G cellular networks: a key enabler to all mobile devices across all industries.

II. Radio Resource management:

Current 4G cellular networks heavily rely on orthogonal frequency-division multiplexing (OFDM) as the signal bearer and the base of associated access schemes. Since OFDM can be used in both frequency-division duplex (FDD) and time- division duplex (TDD) formats, FDD and TDD 4G cellular networks share a similar frame structure by grouping a static number of subcarriers and symb ols into one resource block (RB). Benefiting from the satisfactory subcarrier orthogonality in OFDM, information transmitted in different RBs can be separately decoded at the receivers with limited computational cost. How-ever, it is stubborn to use OFDM to simultane-ously satisfy service requirements from different users with various channel conditions, user termi-nal (UE) capabilities (multiple access support, full duplex mode, feature or smart phones), mobility, frequency bands, and so on. Given that, 5G cel-lular networks aim to introduce new waveforms and provide softer air interfaces. Specifically, fil-ter-bank multi-carrier (FBMC) and unified-filter multi-carrier (UFMC) are famous candidates for Current 4G cellular networks heavily rely on orthogonal frequency-division multiplexing (OFDM) as the signal bearer and the base of associated access schemes. Since OFDM can be used in both frequency-division duplex (FDD) and time- division duplex (TDD) formats, FDD and TDD 4G cellular networks share a similar frame structure by grouping a static number of subcarriers and symbols into one resource block (RB). Benefiting from the satisfactory subcarrier orthogonality in OFDM, information transmitted in different RBs can be separately decoded at the receivers with limited computational cost. How-ever, it is stubborn to use OFDM to simultane-ously satisfy service requirements from different users with various channel conditions, user termi-nal (UE) capabilities (multiple access support, full duplex mode, feature or smart phones), mobility, frequency bands, and so on. Given that, 5G cel-lular networks aim to introduce new waveforms and provide softer air interfaces. Specifically, fil-ter-bank multi-carrier (FBMC) and unified-filter multi-carrier (UFMC) are famous candidates for

4G: all-IP
broadband
4G cellular networks
Voice,
text,
mobile
Internet
connectivity
via phone

Communi
cation,
mobile
Internet,
...
eMBB
~20 Gb/s

Automobil
e,
URLLC,
factory,
1 ms
5G cellular networks
...

mMTC,
200,000/km^2

Metering,
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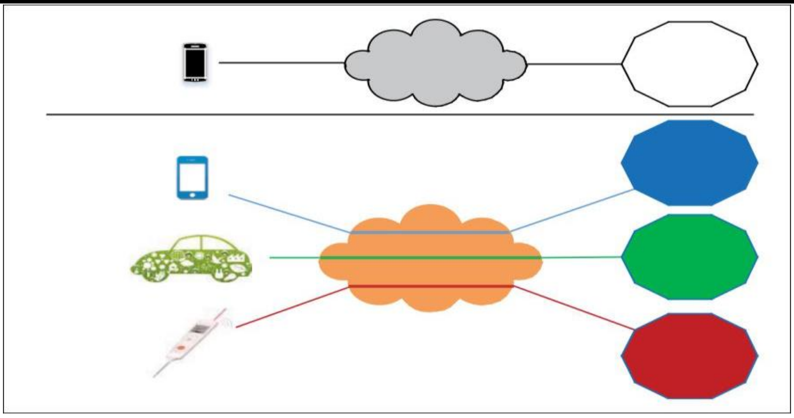

Figure 1. 5G cellular networks: a key enabler to all mobile devices across all industries.

more flexible frame structures and waveforms in the 5G era. As their names imply, FBMC and UFMC both add filters to combat out-of-band leakage across subcarriers and make it unneces-sary to strictly synchronize across RBs. Therefore, 5G cellular networks can provide different air interface solutions in different RBs, in which dif-ferent multiple access schemes, TTI (transmission time interval) parameters, waveforms, and duplex mode, pilot signals, etc., can be well defined [7]. For example, as seen in Fig. 2a, larger bandwidth and symbol length can be applied to eMBB to yield a higher rate, while smaller TTI can be con-figured for URLLC to shorten response latency.

Similar to the evolution from OFDM to FBMC/ UFMC, 5G cellular networks potentially adopt non-orthogonal multiple access (NoMA) schemes such as sparse coding multiple access (SCMA). Such NoMA schemes overlap information from two transmitters in the same radio resource and apply successive interference cancellation (SIC) receivers (or even more computationally-exhaus-tive maximum-likelihood receivers) to decode the received information. Apparently, NoMA could potentially lead to higher throughput. Moreover, another advantage of NoMA is that it makes pos-sible grant-free transmission in the uplink (UL), if the UE identity and the preamble for grant-free UL transmission are mapped together. Instead of waiting for resource allocation commands as in 4G cellular networks, it is feasible to decode the overlapped information from two UEs at the same resources by using SIC receivers. From Fig. 2b, in spite of the reliability advantage for granted trans-mission, grant-free transmission in UL could avoid the cumbersome signaling procedures and save latency for small packets at a trivial performance loss. Comparatively, 5G cellular networks even-tually have one alternative option, which is quite suitable for mMTC service. more flexible frame structures and waveforms in the 5G era. As their names imply, FBMC and UFMC both add filters to combat out-of-band leakage across subcarriers and make it unneces-sary to strictly synchronize across RBs. Therefore, 5G cellular networks can provide different air interface solutions in different RBs, in which dif-ferent multiple access schemes, TTI (transmission time interval) parameters, waveforms, and duplex mode, pilot signals, etc., can be well defined [7]. For example, as seen in Fig. 2a, larger bandwidth and symbol length can be applied to eMBB to yield a higher rate, while smaller TTI can be con-figured for URLLC to shorten response latency. Similar to the evolution from OFDM to FBMC/ UFMC, 5G cellular networks potentially adopt non-orthogonal multiple access (NoMA) schemes such as sparse coding multiple access (SCMA). Such NoMA schemes overlap information from two transmitters in the same radio resource and apply successive interference cancellation (SIC) receivers (or even more computationally-exhaus-tive maximum-likelihood receivers) to decode the received information. Apparently, NoMA could potentially lead to higher throughput. Moreover, another advantage of NoMA is that it makes pos-sible grant-free transmission in the uplink (UL), if the UE identity and the preamble for grant-free UL transmission are mapped together. Instead of waiting for resource allocation commands as in 4G cellular networks, it is feasible to decode the overlapped information from two UEs at the same resources by using SIC receivers. From Fig. 2b, in spite of the reliability advantage for granted trans-mission, grant-free transmission in UL could avoid the cumbersome signaling procedures and save latency for small packets at a trivial performance loss. Comparatively, 5G cellular networks even-tually have one alternative option, which is quite suitable for mMTC service.

MOBILITY MANAGEMENT

Cellular networks have alternative options in the 5G era for access and service provision-ing mechanisms and thus gain the foundation to apply preliminary intelligence. However, 5G cellular networks are still lagging behind what is actually required in practice. First, the number of configurable parameters in a typical 4G node has increased to 1500 from 500 in a 2G node and 1000 in a 3G node [4]. If this trend con-tinues, a typical 5G node is expected to have 2000 or more parameters. Therefore, it is critical to enhance intelligence in the 5G era to realize the self-organizing features (e.g., self-configura-tion, self-optimization, and self-healing). Second, the service types (e.g., eMBB, URLLC, mMTC) defined in the 5G era are static. However, new types of services continually evolve, and the pat-tern in existing services frequently changes as well. In this case, 5G cellular networks still lack functionalities to automatically recognize a new type of service, infer the appropriate provisioning mechanism, and establish the required network slice. Third, 5G cellular networks heavily depend on a centralized network architecture in SDN, and still lack the agility and robustness under the scenario of ever-increasing heterogeneous and complicated cellular networks. To self-orga-nize parameters that become significantly larger, auto-build the network slices for emerging ser-vices, and gain sufficient flexibility for network maintenance, it is essential for cellular networks to observe environment variations, learn uncer-tainties, plan response actions, and configure the networks properly. Coincidentally, AI mainly solves how to learn the variations, classify the issues, forecast future challenges, and find poten-tial solutions, by interacting with the environment. Therefore, cellular networks could leverage the concept of cognitive radio [10] and interact with the environment using AI, so as to fully accelerate the evolution and enter into a brand-new intelli-gent 5G era.

AI has evolved to multi-disciplinary techniques such as machine learning, optimization theory, game theory, control theory, and meta-heuristics

- Among them, machine learning belongs to one of the most important subfields in AI. Usually, depending on the nature of the learning objects and signals to a learning system, machine learning is typically classified into three broad categories:

Supervised Learning: A supervised learning agent will be fed with example inputs and their desired outputs, and aims to determine a general rule that nicely maps inputs to outputs. Super-vised learning has been widely applied to solve channel estimation issues in cellular networks. For example, assume that there exists a wireless chan-nel h, the receiver tries to exploit the transmit pre-amble s and the received signal $y = hs + n_0$ (with n_0 denoting the noise) to estimate h. For such a supervised learning problem, it is common to use probabilistic models to characterize the transition probability $\mathscr{P}(y|s)$ from s to y and take advan-tage of the well known Bayes learning methods to obtain the results. The well known Kalman fil-tering and particle filter methods also play a very important role in optimizing cellular networks.

Unsupervised Learning: Compared to the aforementioned supervised learning, the input information for unsupervised learning does not possess *priori* labels. Therefore, the unsupervised learning agent has to depend on its own capa-bility to find the embedded structure or pattern in its input. Usually, unsupervised learning aims to discover hidden patterns and find the suitable representation in the input data. In the field of AI, unsupervised learning is applied to estimate the hidden layer parameters in neural networks and plays an important role in deep learning meth-ods. Meanwhile, unsupervised learning may be the most widely applied AI category in cellular networks. For example, principal component analysis (PCA) and singular value decomposition (SVD) methods have been used to manipulate the receiving matrix of massive MIMO to reduce the computational complexity. Moreover, 5G NoMA receivers also adopt some factor graph-based methods such as expectation-maximization and message-passing algorithms to achieve lower bit error rate. On the other hand, some classifiers such as the K-means Algorithm are also useful to detect network anomalies.

Reinforcement Learning: Inspired by both con-trol theory and behaviorist psychology, the rein-forcement learning agent could obtain its goal by interacting with a dynamic environment.

RESEARCH DIRECTION IN AI:

s a universal intelligent problem-solving technique, AI can be broadly applied in the design, con guration and optimization for the 5G networks. Speci cally, AI is relevant to three main technical problems in 5G:

Combinatorial optimization: One typical example of the combinatorial optimization problem in 5G NR is the network resource allocation. Given a resource-limited network, an optimized scheme should be gured out to allocate resources to di erent users who share the network such that the utilization of the resource achieves maximum e ciency. As the application of the HetNet architecture in 5G NR with features like network virtualization, network slicing and self-organizing networks (SON), the related network resource allocation problems are becoming more complicated, which requires more e ective solutions.

Detection: The design of the communication receiver is an example of the detection problem. An optimized receiver is able to recover the transmitted messages based on the received signals, achieving minimized detection error rate. Detection will be challenging in 5G within the massive MIMO framework.

Estimation: The typical example is the channel estimation problem. 5G requires accurate estima-tion of the channel state information (CSI) to achieve communications in spatially correlated channels of massive MIMO. The popular approach is the so-called training sequence (or pilot sequence), where a known signal is transmitted and the CSI is estimated using the combined knowledge of the transmitted and received signal.

Many researches have already been done for the application of AI in 5G as in literatures [15{23]. However, due to the limitations of both the communication systems and AI, some of the applications may be restricted. Firstly, after years of research and test, conventional methods have shown their abilities to handle the communication systems. A complete framework with conventional techniques have been formed, which is e ective, mature and easy to implement for real world scenarios. Secondly, the capacity of a communication system is constrained with certain upper bounds (e.g., the Shannon limit), and some of the well-designed methods can reach near-optimal performance su ering negligible loss with respect to the capacity bound. For example, in [24] a transmitter optimization method for MIMO is proposed based on an iterative water- lling algorithm, which closely achieves near-Shannon performance in the general jointly correlated MIMO channels. This kind of methods will not be over-performed by even the most-advanced AI technique. Moreover, there're still obstacles to apply AI learning in real-world problems due to the convergence issues for training. Careful checks should be done to make sure the optimal

III. PREPARE YOUR PAPER BEFORE STYLING

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