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An intelligent wireless transmission toward 6G

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Abstract: With the deployment and commercial application of 5G, researchers start to think of 6G, which could meet more diversified and deeper intelligent communication requirements. In this paper, a four physical elements, i.e., man, machine, object, and genie, featured 6G concept is introduced. Genie is explained as a new element toward 6G. This paper focuses on the genie realization as an intelligent wireless transmission toward 6G, including sematic information theory, end-to-end artificial intelligence (AI) joint transceiver design, intelligent wireless transmission block design, and user-centric intelligent access. A comprehensive state-of-the-art of each key technology is presented and main questions as well as some novel suggestions are given. Genie will work comprehensively in 6G wireless communication and other major industrial vertical, while its realization is concrete and step by step. It is realized that genie-based wireless communication link works with high intelligence and performs better than that controlled manually.

Key words: 6G; man-machine-object-genie; sematic information; end-to-end AI transceiver; AI empowered wireless transmission; user-centric access

1 Introduction

With the 5G standardization Release 16 frozen in July 2020, 5G wireless communication enters the fully implementation and commercial application era worldwide, which empowered many major industry vertical development. Although the 3rd Generation Partner Project (3GPP) is now studying 5G enhancement Release 17, research on systems and techniques beyond 5G had been started early in 2017[1]. Along with 5G commercial application, vision of 6G and emerging technologies draw more and more attentions from then on.

The newest publication of Tataria et al.[2] studies the vision of 6G systems and its use cases by summarizing and analyzing some previous research on 6G[3−7]. It shows the 6G vision from eight key performance metrics[2] as (1) peak rate (≥1 Tbps); (2) user experience rate (1 Gbps); (3) latency (25 μs to 1 ms); (4) mobility (1 000 km/h); (5) area capacity (1 Gbps/m^2); (6) connectivity (10^7 devices/km^2); (7) reliability (99.999 999%); (8) network energy efficiency (100−1000×). The use cases and techniques[2, 4, 6] cover holographic communications, tactile and haptic internet application, network and computing convergence, extremely high rate information showers, connectivity for everything, chip-to-chip communications, and space-terrestrial integrated networks. References [8−10] introduces 6G oriented techniques from network to physical layer (PHY) aspect. One common feature from key techniques point of view is that artificial intelligence (AI) would empower wireless communication system from network as mobile computing and resource management to wireless access, and radio transmission[11−14], while analyzes big data features in wireless networks and action in wireless AI to enhance intelligence. Therefore the main feature of 6G compared to 5G is that 6G is more intelligent as it

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could study new cases by data analysis and change mechanisms accordingly. We call that 6G is empowered by an intelligent element genie[15], and is constructed by four physical elements as man, machine, object, and genie, which could work coordinately to reach 6G key performance indicators (KPIs). This concept of 6G is from the top-level as it reveals the feature for all kinds 6G senarios and use cases, however the concrete techniques may be different for different deploy systems to meet the requirements of 6G KPIs. For instance, to realize peak rate larger than 1 Tbps, THz communication and visible light communication could be candidate key techniques. While to realize network energy efficiency enhanced by 100−1000×, green communication techniques draw more attention as intelligent reflecting surface (IRS), and energy harvesting. On the top of the different scenarios and techniques, genie element could make the system work more efficient by empowered them with intelligence.

This paper presents 6G concept as whatever the scenario is, the system would be constructed by four physical elements, i.e., man, machine, object, and genie. By collaboration of man, machine, object, and genie, the system, such as mobile communication, Internet of Things (IoT), Internet of Vehicle (IoV), etc. would work with high intelligence, security, and performance.

The rest of the paper is organized as follows. In Section 2, the genie element in 6G is explained. Section 3 introduces how to realize genie from information theory transmission aspect as Sematic Information Theory. Sections 4 and 5 show the genie exploitation in PHY techniques. In Section 4, a joint intelligent transceiver design is deployed with its challenges, which seems a long way from current 5G radio transmission systems. Section 5 reviews the state-of-the-art enhancement techniques by AI to realize genie feature to different PHY modules, which is more prospective to improve the current 5G PHY techniques. A conclusion is shown in Section 6.

2 Genie: New element in 6G

The deployment and implementation of 5G have bought remarkable changes to modern wireless communication systems. 6G will be further expanded and upgraded to meet more diversified and deeper intelligent communication demands. Trends on the horizon —such as the broad application of AI in 6G —call for a radical rethink about the design of future wireless architectures. To empower AI as a super oracle, services in 6G will evolve into two setups: the real world and the virtual world. The real world is compatible with current communication scenarios and infrastructures in 5G, while the virtual world extends the real-world services, dealing with novel virtual-world requirements. Accordingly, in addition to the three physical elements, i.e., man, machine, and object, 6G should also embrace a new element—genie[14]. Genie belongs to the virtual world and allows communication and decision-making without human intervention. Relying on a large real-time collection of data and state-of-the-art machine learning techniques, genie is able to capture the user's intentions and make decisions. Genie overrides the cohesive integration of man, machine, and object and can cover any physical entities that act as communicating and computing nodes. Through the harmonious collaboration with man, machine, and object, genie can provide users with immersive virtual scenes and be granted to make decisions on behalf of users. Real-virtual combination, real-time interaction, and other features of the virtual world have brought severe challenges to 5G. To support those pressing demands of 6G, novel basic theories and techniques are eagerly anticipated. Genie is a concept related comprehensively to every corner of wireless communication systems. Semantic communication, which is expected to be the genie for 6G, is just such a worthwhile research direction and an untapped treasure relating information communication theory. AI empowered wireless transmission or end-to-end AI design mechanics of transmission is another concrete directions driven by the concept of genie. In general, genie is a combination result of optimization theory, automatic control, machine learning, and data science. Genie is realized by different mechanics in different protocol aspects in wireless communications.

3 Sematic information theory

From the viewpoint of epistemology, information is embodied through the perception of the cognitive subject (man, machine, and object) and comprises three levels, i.e., syntactic, semantic, and pragmatic, as shown in Fig. 1 , where syntactic information is the most underlying level and pragmatic information is the most complicated one. It is essentially consistent with the three levels of communication problems mentioned by Weaver in 1949[16]. Classical Shannon's information theory[17] only investigates syntactic information, or more specifically, probabilistic information in syntactic information, excluding semantic and pragmatic. According to Weaver[16], Shannon's information theory only solves the technical problem of how accurately the communication symbols can be transmitted.

3.1 Semantic concept exploration

In recent years, the research on semantic information has aroused an academic upsurge. Semantic information reflects the inherent meaning of the moving and changing states of an object. It can be comprehended and interpreted with natural language, thus highly subjective. From syntactic information to semantic information, it will provide a new perspective for communication system optimization and have great revolutionary significance. In fact, the exploration of semantic information theory has been a long-standing topic. With Weaver as the pioneer, many researchers have devoted themselves to lay the foundation of semantic information theory. Carnap and Bar-Hillel[18, 19] put forward the conceptual framework of semantic information theory, attempting to supplement the traditional communication theory. They believed that the semantic information contained in a sentence should be defined based on the logical probability of the content. Barwise and Perry[20] further proposed the situation logic principle to describe semantic information. In Ref. [21], Floridi proposed the strongly semantic information theory and pointed out the Bar-Hillel and Carnap paradox that a self-contradictory sentence carries more semantic content. In 2011, D' Alfonso[22] introduced the notion of truth likeness to quantify semantic information. Although it has been ardently discussed, semantic information theory is still in its infancy, and there is no universal agreement on the corresponding definition and measurement. In recent decades, fruitful advances in cognitive neuroscience have greatly influenced neural networks and deep learning theory. How to measure, extract, and represent semantic information has attracted more and more attention from academia and industry.

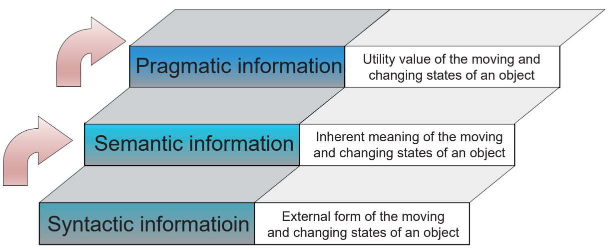

Fig. 1 Three levels of information.

3.2 Semantic measurement

As aforementioned, semantic information not only depends on the sender, but the receiver's understanding, so it is both random and fuzzy. Shannon's information theory puts a great emphasis on probability, regardless of the specific content and meaning of information. It describes the randomness of information by the notion of probabilistic entropy whereas natural language descriptions, i.e., semantics, are typically fuzzy in reality. Therefore, to characterize and analyze semantic descriptions, such as heavy, light, probably, nearly, etc., we should resort to fuzzy set theory. De Luca and Termini[23, 24] first studied the indefiniteness arising from pure fuzziness and introduced the definition of entropy of a fuzzy set, formally similar to the Shannon entropy although different conceptually. On this foundation, Wu[25] went a step further and put forward the concepts of generalized joint entropy, generalized conditional entropy, and generalized mutual information, establishing a primary semantic measurement scheme. Let $X=\{x_i: i=1,2,\ldots,N\}$ denote a discrete probabilistic random source, the Shannon entropy is defined as the average self-information on the probability measure P_X and is given by

$$H(X)=\sum_{i=1}^{N}P(x_i)\log_2 P(x_i) \tag{1}$$

Given a complete fuzzy set ensemble $\tilde{X}=(\tilde{X}_1,\ldots,\tilde{X}_K)$, let the membership function μ measure the degree of fuzziness and $\sum_k \mu_{\tilde{X}_k}(x_i)\leqslant 1$, the generalized source entropy is defined as

$$\begin{aligned}\tilde{H}\left(\tilde{X}\right)&\triangleq -\sum_{i=1}^{N}\sum_{k=1}^{K}\mu_{\tilde{X}_k}(x_i)P(x_i)\log_2\mu_{\tilde{X}_k}(x_i)P(x_i)=\\ &H(X)+\sum_{i=1}^{N}P(x_i)h_{\tilde{X}}(x_i)=\\ &H(X)+H\left(\tilde{X}\right)\end{aligned} \tag{2}$$

where $h_{\tilde{X}}(x_i)=\sum_{k=1}^{K}\mu_{\tilde{X}_k}(x_i)\log_2\mu_{\tilde{X}_k}(x_i)$ denotes the pure fuzzy entropy when the event x_i occurs. According to Eq. (2), the generalized source entropy consists of two parts, the probabilistic entropy and the fuzzy entropy. The former measures the probabilistic incertitude while the latter represents the uncertainty of intrinsic ambiguity, i.e., semantic uncertainty.

Ideally, given a source and its probability measure, the above generalized entropy can be calculated by carefully selecting a membership function μ. However, since semantic information is always contained in syntactic information, and μ is usually nonlinear and intractable and may vary dynamically, the theoretical result in Eq. (2) cannot offer practical guidance for semantic communications. Thanks to the rapid development of deep learning, Niu et al.[26] proposed the idea of semantic base, which extracts semantic features of the source with the aid of neural networks for semantic information measurement. In this way, the difficulty of selecting μ is avoided. Actually, there have been some early studies on practical semantic communications. A deep learning enabled semantic communication system was established in Ref. [27] for text sources. Farsad et al.[28] designed a bidirectional long and short term memory (Bi-LSTM) model based semantic coding scheme. As for image sources, several analog semantic coding schemes using convolutional neural networks (CNN) were presented in Ref. [29−31] and were proved capable of compressing images efficiently and resisting wireless errors. For diverse communication scenarios in 6G, since various individuals (man-machine-creature-genie) deliver massive heterogeneous types of data, comprehensible semantic communications will play a critical role by virtue of its intelligence and become a promising trend. Even so, the modeling and evaluation of semantic entropy, channel capacity, and rate distortion function is still an open problem, and research on semantic information theory still has a long way to go.

4 End-to-end AI joint transceiver design

Communication is a complex and mature engineering field with many distinct areas of investigation which have all seen diminishing returns with regards to performance improvements, in particular on the physical layer[32]. In addition, in domains such as computer vision and natural language processing, deep learning (DL) shines because it is difficult to characterize real world images or language with rigid mathematical models. From the information point of view, which comes from language, image, video, etc., it also employs the same features and obstacles as those of natural language processing (NLP) and computer vision (CV). Therefore, in recent years, research on the joint transceiver design based on deep learning has attracted considerable attention.

DL was first introduced to the physical layer in Ref. [32]. By interpreting a communications system as an auto-encoder (AE), Ref. [32] developed a fundamental new way to think about communications system design as an end-to-end reconstruction task that seeks to jointly optimize transmitter and receiver components in a single process and extended the networks of multiple transmitters and receivers. The neural networks in Refs. [32, 33] only used linear fully connected layers to achieve competitive accuracy with respect to traditional schemes relying on expert features. Soon afterwards, a novel CNN-based auto-encoder communication system is proposed in Refs. [34, 35], which can work intelligently with arbitrary block length according to different channel environments. A DL auto-encoder is presented in Ref. [36] where both the transmitter and receiver employ the bi-directional gated recurrent unit (Bi-GRU) layers for end-to-end physical layer communications, in the presence of inter symbol interference (ISI). GRU is a variant of long short-term memory (LSTM) in order to reduce neural networks parameters. LSTM has been widely applied in various physical layer cases, such as the joint deign of source-channel coding[28]. The above DL is mainly used in point-to-point communication systems. Of course, DL can also be extended to multiple-input multiple-output (MIMO) and multi-user scenarios. References [37−39] presented a novel physical layer scheme for MIMO communication systems based on unsupervised DL using an auto-encoder in an interference channel (IC) environment. The study in Ref. [32] proposed a solution for the interference of a two-user link when AE is applied. However, only two users are considered, and offline training is used. Reference [40] addressed the dynamic interference in a multi-user Gaussian interference channel and proposed a novel adaptive DL based AE to learn and predict dynamic interference and update the leaning processing for the decoder.

In wireless communication systems, the receiver has to work with noise and interference corrupted versions of transmit symbols. The auto-encoders discussed above are not designed to work with latent codes corrupted with noise. Therefore, Refs. [41, 42] provide a framework called variational auto-encoder to design end-to-end communication systems which accounts for the existence of noise corrupted transmit symbols. The objective function for optimizing these models was derived based on the concepts of variational inference.

The implement of the end-to-end auto-encoders discussed above is in the case where the channel parameters are known in advance and the channel is assumed to be differentiable. When the channel parameters are unknown in advance, the gradients cannot back propagated through the unknown channel, which forestalls the learning of the end-to-end networks[43]. We will introduce two methods to address the issue. In Ref. [44], a reinforcement learning (RL) based approach has been proposed to circumvent the problem of missing gradients from channels when optimizing the transmitter. In order to solve the missing gradient problem and lower the demands for the large amount of training data, a generative approach based on conditional generative adversarial net (CGAN) has been proposed in Ref. [45].

Existing work has shown the power of data-driven models in the joint transceiver design. Even though a universal transmitter/receiver can be optimized in the end-to-end learning-based communication design, the training process takes very long as all the communication blocks are merged[43]. In order to improve the training efficiency and achieve good system performance, part of the communication blocks can be kept and model-drive DL methods can be considered[46, 47].

5 Intelligent wireless transmission model design

5.1 Channel estimation

In recent years, the rapid development of AI has led to breakthroughs and innovations in many technical fields. The combination of DL and wireless communication is considered to be an important cornerstone for 6G intelligent communication. Channel estimation is an important part of wireless communication system. Some traditional channel estimation algorithms, such as least square (LS), minimum mean square error (MMSE), have been widely used in the field of channel estimation. AI empowered channel estimation technology aims to introduce deep neural network (DNN) into the traditional channel estimation algorithm, which can effectively improve the accuracy of channel estimation, especially in the situation of limited pilot resources.

For the channel estimation with DL, most of the researches in recent years are based on CNN to build neural network model[48−53]. The reason can be attributed to that in massive MIMO system, the channel response matrix can be regarded as two-dimensional image, and the process of channel estimation can be compared with the process of image reconstruction and denoising using CNN. Among them, Ref. [48] proposed a CNN channel estimation network based on image super-resolution, which takes the channel estimated by traditional LS algorithm as the input of the network and makes the output of the network close to the real channel response, which could be interpreted as the high-resolution image. To eliminate the influence of noise on channel estimation, Refs. [49, 50] use convolutional non-blind denoising network. To further reduce the overhead of pilot based channel estimation, a convolution generative adversarial network (C-GAN) is proposed, which achieves good results in the scenario of receiving pilot one-bit quantization with analog-to-digital converters (one-bit ADCs)[51]. To improve the efficiency of neural network training, attention mechanism and complex neural network model are introduced on the basis of convolutional residual network[52]. On the other aspect, according to the time-varying characteristics of wireless channel, some researches build network models based on recurrent neural network (RNN)[54, 55]. A network combining LSTM with multi-layer perceptron (MLP) is proposed[54], which achieves good results in high-speed mobile scenarios. The RNN network model is optimized in Ref. [55] to get higher channel estimation accuracy than the traditional linear minimum mean square error (LMMSE) algorithm.

It is worth noting that most of the current researches on channel estimation empowered by deep learning considers the friendliest scenarios with few antenna ports (less than 8) and rich pilot resources, which is not in accordance with 5G NR reference signal as channel state information–reference signal (CSI-RS)[56] with massive MIMO (more than 64 antenna ports). For example, a 2×2 MIMO scenario with a simple comb pilot structure is used for channel estimation in Ref. [57]. After interpolation, a three-layer fully connected neural network is used for optimal fitting. The simulation results show that the neural network has a certain performance improvement compared with the traditional scheme. For large-scale MIMO antenna with more than 64 ports in 5G NR, according to the resource allocation rule of CSI-RS in resource blocks (RBs)[56], the frequency band resource occupied by each port pilot decreases with the increase of the number of ports. Therefore, for all subcarriers in the whole band, the placement of each antenna port pilot is extremely sparse, which greatly deteriorate dramatically the performance of traditional channel estimation. AI is expected to improve the channel estimation results. However more studies are needed to design effective and lightweight neural network to tackle the channel estimation problems with very sparse pilot assignment in massive MIMO cases. Figure 2 is a summary of the DL-based channel estimation algorithms introduced above.

5.2 Signal detection

In this section, we discuss the application of AI techniques to improve signal detection. In MIMO systems, the goal of signal detection is to determine the transmitted signal vector $\boldsymbol{s}$ from the received vector $\boldsymbol{y}=\boldsymbol{H}\boldsymbol{s}+\boldsymbol{n}$. $\boldsymbol{H}$ represents the channel matrix between the transmitter and the receiver and $\boldsymbol{n}$ is a Gaussian noise vector. This can be achieved by classical signal detection algorithms such as the optimal maximum likelihood (ML), near-optimal spherical decoding (SD), and suboptimal linear zero-forcing (ZF) and MMSE. They are mathematical model based algorithms, which have many disadvantages, including high complexity and poor scalability. In recent years, signal detection algorithms based on DL are widely concerned. Research shows that DL technology can significantly improve the performance of signal detection compared with the classical detector[33].

Existing literature research shows that signal detection can be divided into two categories: data driven and model driven, as shown in Table 1. The data

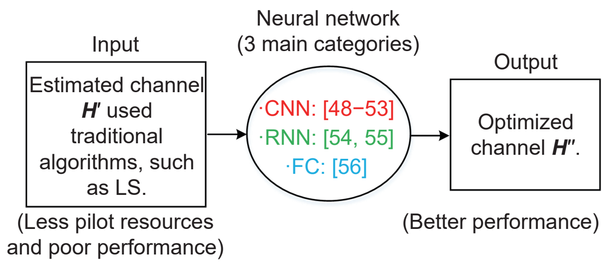

Fig. 2 DL-based channel estimation.

Table 1 Classification of existing DL algorithms.

DL group	Detector	Reference	DL models
Data driven	DL model	[33, 58, 59]	DNN, CNN, RNN
Model driven	PGD-based	[60, 61]	DetNet
	Iterative algorithm	[62, 63]	OAMP-Net
		[64]	MMNet
	SD	[65]	FS-Net
	TS	[66]	FS-Net

driven AI signal detector is constructed by neural network totally, such as DNN[33], CNN[58], and RNN[59]. Relying on the data of wireless communication systems, through training, the output result is the estimated value of the transmitted signal. Reference [33] used DNN to solve the problem of signal detection in orthogonal frequency division multiplexing (OFDM) system. It regards channel estimation and signal detection as a whole and is directly realized by DNN. Reference [58] proposed a deep fully CNN, which combines the channel estimation and signal detection modules in a 5G-compliant fashion and using 3GPP-defined channel models. Reference [59] utilized a RNN with Bi-LSTM architecture to achieve signal detection in uplink OFDM systems over time-varying channels.

The model driven AI signal detector combines classical signal detection model and deep leaning algorithms. In most cases, classical iterative signal detection algorithms are reconstructed and expanded into the form of network, and parameters are dynamic and could be trained by communication data. Therefore the detector is optimized. References [60, 61] considered the application of DL in MIMO system. Based on the ML detection algorithm, the projection gradient descent (PGD) method is expanded to obtain the detection network (DetNet). DetNet can achieve high accuracy with significantly lower complexity. Based on orthogonal approximate message passing (OAMP) iterative algorithm and combined with deep learning network, OAMP-Net is proposed in Refs. [62, 63]. The network solves the problem of signal detection performance degradation of OAMP algorithm in complex MIMO systems. On real-world channels with spatial correlation, Ref. [64] proposed Mehrdad-Mohammad network (MMNet), which builds on the theory of iterative soft-thresholding algorithms. That algorithm utilizes temporal and spectral correlation in real channels to accelerate training. Reference [65] was the application of DL to SD detection in large MIMO systems. Different from the idea of developing iterative network based on detection algorithm in Refs. [62−64], Ref. [65] used a fast-convergence sparsely connected detection network (FS-Net) to generate the initial solution of detection algorithm. The results show that compared with the detection network executing SD algorithm in the training phase, the algorithm proposed in Ref. [65] has lower complexity without any performance loss. Reference [66] was the application of DL to tabu search (TS) detection in large MIMO systems. Reference [66] used the FS-Net to generate an initial solution and then executed TS algorithm. The DL-aided TS algorithm reduces the complexity by 90% and maintains the same performance as the traditional TS algorithm. The suboptimal initial solution can accelerate the search process of the traditional detection algorithm without affecting the final optimal solution, and does not need to train the algorithm parameters. They perform better in algorithm complexity and performance.

Data driven AI signal detector has obvious advantages when CSI is not available. However, there are some problems in this kind of detector. They rely heavily on network construction and experience parameter adjustment by training. Although they are better than classical detectors in some cases, their performance is far from optimal, especially in more complex communication scenarios. Model driven AI signal detectors are proposed in order to overcome the above problems. The combination of neural network and classical iterative detection algorithm can significantly reduce the complexity of the algorithm while ensuring the performance of the detector. The network setting, parameter training, and subsequent optimization expansion of the detector are interpretable due to mathematical optimization based on communication model. Therefore, signal detector based on model driven neural network gains more feasibility. However, the complexity and lightweight design with better detection performance is still hard to resolve especially for variant mobile terminals. Table 1 shows the classification of the existing DL-based signal detection algorithms.

5.3 AMC and automatic modulation detection

Adaptive modulation and coding (AMC) technology can timely adjust the modulation and channel coding rate of wireless link transmission according to the change of communication environment[67], so as to balance the quality and efficiency of wireless transmission. The traditional AMC technology is to establish a modulation and coding scheme (MCS) look-up table by feedback signal-to-noise ratio information under the condition that the system block error rate (BLER) is lower than a specific value, and then select the appropriate MCS for the next transmission time interval (TTI) according to the corresponding look-up table of the current CSI in the actual communication system. However, the relationship between channel quality and system performance is not a simple linear correspondence, and the transmission effect is poor[68]. With the advent of AI era, machine learning is exploited to make AMC more accuracy and efficiency. The simple mapping operation of channel quality indication (CQI) and MCS is improved by introducing AI algorithms to improve the mapping accuracy of current channel state and CQI[69], so as to gain lower BLER and higher spectrum efficiency. Machine learning and AI are potential to automatically recognize different modulation signals without signaling assistance, which can reduce the signaling overhead of AMC technology to a certain extent[70].

The throughput performance of AMC based on the traditional look-up table method and four machine learning solutions are shown in Fig. 3[71]. It can be seen that the performance of the traditional look-up table method is the worst because signal to interference plus noise ratio (SINR) estimation algorithms can only violently project multiple SINRs in a communication

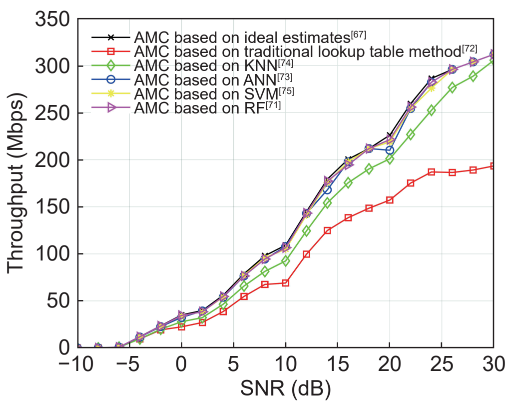

Fig. 3 Throughput performance of multi AMC scheme model.

link to a single value while this process is bound to ignore or weaken the relationship between multiple SINRs. The introduction of machine learning has greatly improved this disadvantage. The machine learning method uses multiple SINRs as input features, uses different algorithms to determine the CQI label, and uses the input features as the overall input, which results in better throughput performance.

To sum up, machine learning and AI could make AMC smarter. Inspired by this, wireless transmission link parameters could be adjusted dynamically and efficiently by AI. However it is still an open research issue due to de complexity of effects of parameters.

6 User centric intelligent access

6.1 User centric cell free concept

Integrated massive MIMO seems to foresee its performance increasing ceiling by enlarging antennas arrays. Network densification with the deployment of large number of access points (APs) per unit area is a way to improve the network coverage and capacity, which implies more potential in quality of experience (QoE) increasing for 6G. To further alleviate the increased signal interference and outage problem of the cell-edge users, a promising concept has been recently termed as the so-called Cell-free (CF) massive MIMO systems, which comprise a large number of distributed, low cost, and low power AP antennas, connected to a network controller[76]. The number of antennas is significantly larger than the number of users. The system is not partitioned into cells and each user is served by all AP antennas simultaneously, which can provide a more uniform service level to the users than a conventional cellular topology. A user-centric (UC) approach to CF massive MIMO is recently proposed[77], wherein each user is served only by a limited number of APs. In other words, the active APs within the same cooperation set serve a specific subset of user equipment (UE), which provide rewarding connectivity patterns, while the other APs without served UE will run in sleep mode for reduced power consumption. The UC approach requires less backhaul overhead than the conventional CF approach, and outperforms the latter in terms of achievable rate and energy efficiency for some cases. The expressions for the downlink (marked d in the upper right corner) feasible rate per user unit bandwidth, spectrum efficiency per user, sum spectrum efficiency, and energy efficiency are given respectively below:

$$R_k^d = \log_2\left(1+\frac{\left(\sum_{m=1}^{|A_k|}\sqrt{p_{mk}\gamma_{mk}}\right)^2}{\sum\limits_{k'\in\prod_k\backslash\{k\}}\left(\sum_{m=1}^{|A_{k'}|}\sqrt{p_{mk'}\gamma_{mk}}\right)^2+\sum_{k'=1}^{K}\sum_{m=1}^{|A_{k'}|}p_{mk'}\beta_{mk}+\sigma_{\mathrm{DL}}^2}\right) \tag{3}$$

$$SE_k^d = \left(1-\frac{\tau_p}{\tau_c}\right)\times R_k^d \tag{4}$$

$$SE_{\mathrm{sum}}^d = \sum_{k=1}^{k} SE_k^d \tag{5}$$

$$E_e = \frac{B\cdot SE_{\mathrm{sum}}^d}{\sum_{m=1}^{|A_k|}\sum_{k=1}^{K}\varDelta_m p_{mk}+\sum_{m\in A}P_m+B\sum_{m\in U_m}\sum_{k=1}^{K}P_{tb,m}R_k^d} \tag{6}$$

where K represents the number of users, $p_{mk} \geqslant 0$ is the transmit data power that AP m-th allocates to user k, γ_{mk} is the channel estimate variance, $\prod_k$ represents the user set using the same pilot sequence as user k, $\prod_k \backslash\{k\}$ denotes the user set using the same pilot sequence as user k except user k, β_{mk} denotes the large-scale fading coefficient, τ_c is the length of coherence time, τ_p is the length of uplink training, B is the system bandwidth, $\varDelta_m \geqslant 1$ determines the inefficiency of the power amplifiers, P_m models the power consumption of the transceiver chain connected to active APs and the traffic-independent power of the front haul connections and baseband processing, $P_{tb,\ m}$ (measured in Watt per bit/s) is the traffic-varying power consumption of the front haul and baseband processing, A_k denotes the APs selected by the k-th user, A denotes all the active APs, U_m is the UEs served by the m-th AP, and σ_{DL}^2 is the variance of the additive Gaussian noise of the downlink channel.

6.2 Intelligent access point selection

One of the main issues of UC-CF system is the AP selection (or initial access), since a fraction of the APs can beneficially communicate to a specific UE[78]. Specifically, we consider a CF massive MIMO system where M APs serve K users in the same time-frequency resource under time-division duplex (TDD) operation. Each AP is equipped with N antennas, while each user has a single antenna. We further assume that $M >> K$. Herein, for a specific user k, how to choose a suitable service AP set is the key to improve the system performance. This is a meaningful research topic, and many scholars have done some research in this area. For example, with an unconstrained sub-parameterization method based on large-scale fading coefficients[79], the k-th user is associated with only $|A_k| \leqslant M$ APs corresponding to the $|A_k|$ largest large-scale fading coefficients. Naturally, we can choose $|A_k|$ APs which satisfy

$$\sum_{m=1}^{|A_k|}\frac{\bar{\beta}_{mk}}{\sum_{m'=1}^{M}\beta_{m'k}} \geqslant \delta\% \tag{7}$$

where $\{\bar{\beta}_{1k},\bar{\beta}_{2k},...,\bar{\beta}_{Mk}\}$ is the sorted (in descending order) set of the large-scale fading set $\{\beta_{1k},\beta_{2k},...,\beta_{Mk}\}$, and δ is a scale threshold. Another type of AP selection scheme is the so-called received-power-based selection[80]. The goal of this method can be the optimization of sum rate or energy efficiency. After obtaining the power allocation coefficients, we can set a threshold to disconnect the connections between the UE and AP whose power is lower than the threshold, or we can select the AP according to the following formula[81]:

$$\sum_{m=1}^{|A_k|}\frac{\bar{p}_{mk}}{\sum_{m'=1}^{M}p_{m'k}} \geqslant \delta\% \tag{8}$$

where $\{\bar{p}_{1k},\bar{p}_{2k},...,\bar{p}_{Mk}\}$ is the sorted (in descending order) set of the power set $\{p_{1k},p_{2k},...,p_{Mk}\}$. We can adopt some sub-automation tools, such as Matlab CVX toolkit to obtain the power allocation coefficients. Reference [82] proposed a dormant strategy to turn off some APs to improve energy efficiency. They solved the joint optimization problem of AP selection and power allocation in a given downlink service demand scenario, and obtained a global optimal solution of AP selection strategy and transmit power by solving the mixed- integer second-order cone program, which can greatly improve the energy efficiency of the system.

They further gave a simplified algorithm based on binary search to reduce the computational complexity. The effect of these algorithms in improving energy efficiency is shown in Fig. 4 by simulation. We use "AAO" to indicate all APs on method, use "OPT" to represent the optimal algorithm with high computational complexity, and use "SIM" to represent the simplified algorithm with low complexity. It can be observed that the energy efficiency of the CF network used by these optimum algorithms (fewer APs but favorable connections) can be increased compared with that all APs always keep active.

It is worth noting that the selection of AP is affected by many factors, such as the channel model with disparate physical coefficients, location distribution of UEs and APs, number of network devices, etc., and is also depended on the system optimization objects (sum rate or energy efficiency). Since intelligent machine learning, such as deep learning methods in Refs. [81, 83, 84], deep reinforcement learning in Ref. [85], is good at dealing with complex problems containing large amounts of data and multiple variables (coefficients in the system), it is expected to solve the problem of AP selection in CF massive MIMO systems more effectively. The brief framework is shown in Fig. 5.

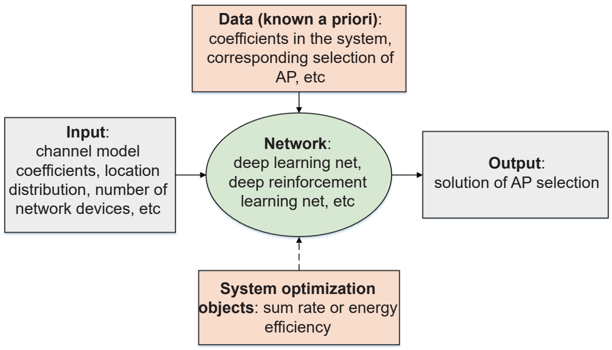

Fig. 5 Framework of intelligent AP selection.

7 Conclusion

This paper presents a major characteristic of genie in 6G in addition to the three physical elements from 5G, i.e., man, machine, and object, to reduce manual work and increase machine intelligence. Although genie is a new element from virtual world view, it acts as intelligence mechanism by different techniques for wireless communication systems. This paper focuses on the genie realization aspect on physical layer of wireless communications, which makes a radio transmission link working automatically with high intelligence and efficiency. For information transmission, sematic information theory is expected to break the limitations from normal Shannon theory to improve spectrum efficiency by intelligent sematic information processing. For wireless signal transmission, AI is embraced by transmitter and receiver design with different granularities, from total end-to-end AI transceiver design to parameter optimization by deep learning in channel estimation, signal detection, AMC, etc. The 6G research is just beginning and there are many open questions presented in each sections related to intelligent wireless transmission technologies. From MAC layer, RRM layer, network layer, and application layer, Genie introduces different novel mechanisms, which is out of the scope of this paper. In general, genie makes a great and systematic concept for 6G systems to work with high intelligence and performs better than that controlled manually. Genie works comprehensively in 6G wireless communication and other major industrial vertical, while its realization is concrete and step by step.

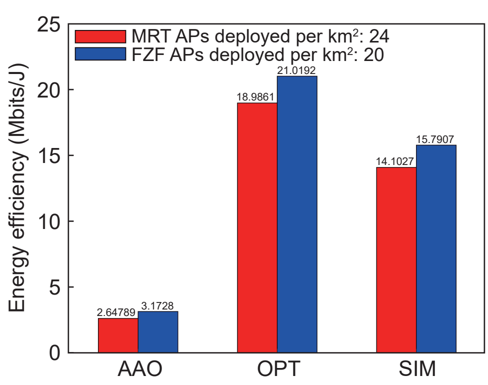

Fig. 4 Energy efficiency of different AP dormant strategies.

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BUPT contribute ideas and information in Sections 5 and 6.1.

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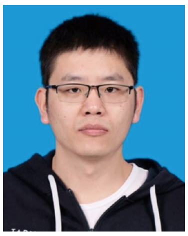

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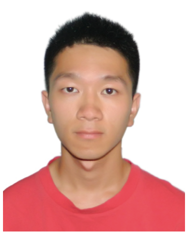

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