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Energy-efficient and high-spectrum-efficiency wireless transmission

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Abstract

With the deployment and commercialization of the fifth-generation (5G) mobile communication networks, the access nodes and data volume of wireless networks are showing massive and explosive growth. In this paper, we firstly review the research progress on the energy-efficient and spectrum-efficient wireless transmission, from the perspectives of both latency and energy consumption. We then provide several solutions to high-efficiency wireless transmission for the 5G wireless networks. Finally, we give some discussions about the future road for the design of energy-efficient and spectrum-efficient wireless transmission, which provides some theoretical reference for the system design of wireless networks and Internet of Things (IoT) networks.

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1. Introduction

The mobile communication system that has been updated for ten years has now reached the fifth-generation (5G). It has evolved from the narrow-band analog communication system in the 1980s to the advanced broadband digital communication system. The supported applications have also extended from pure voice communication to enhanced mobile broadband (EMBB), large scale machine type communications (MMTC) and ultra reliable and low latency communications (URLLC) [1–4]. Mobile communication has completely changed the world and has a profound impact on people's lives. Since 5G was put into commercial use in 2019, a large number of new mobile communication services have emerged, such as ultra-high definition video, extended reality (including virtual reality, augmented reality, etc.), large-scale Internet of Things (IoT) communication and automatic driving, enabling people to enjoy the convenience, efficiency and fun brought by the digital world. Advanced communication technology has given birth to a wealth of mobile Internet and industrial applications, and the higher communication requirements of these applications have driven the evolution and development of communication technology. At present, 5G is deployed in a global fashion, but industry researchers have begun to look forward to and study the communication vision and related candidate technologies of the next generation mobile communication system facing the future 2030 [5–7]. The sixth-generation (6G) mobile communication system will evolve from 5G Internet of everything to intelligent connection of everything, create an all digital intelligent society, and enable smart, efficient and green production and life style.

New services and new demands are the internal driving force for the evolution of communication technology. In the 6G era, the equipment access density will reach an astonishing $10^7/\text{km}^2$, and the peak transmission rate will exceed 1Tbps [4]. Such massive equipment deployment and big data transmission will bring explosive growth in data traffic. According to the prediction of the International Telecommunication Union (ITU)[8, 9], the global communication flow will reach 5000EB in 2030. There is no doubt that the super large-scale equipment access and massive data transmission put forward super high demands for the energy efficiency and spectrum efficiency of 6G network. On the other hand, the scarcity of spectrum and huge communication energy consumption have become important bottlenecks restricting the development of wireless communication. In order to reduce carbon emissions and achieve carbon neutrality, green and sustainable development has been regarded as an important goal of 6G network and terminal design.

2. Analysis of the current state of research

Energy-efficient and spectrum-efficient wireless transmission is the key to realize B5G edge intelligence network, but wireless transmission also presents the shortcomings of high energy consumption, high equipment cost and low spectrum utilization. To address the advantages and shortcomings of wireless transmission, researchers have systematically conducted in-depth research from multiple perspectives on the core performance indicators of wireless transmission such as rate, delay, and energy consumption, and have achieved fruitful research results.

We should study the energy-efficient wireless transmission for future networks. Previous work has targeted multi-cell MIMO wireless communication systems, combined with finite caching techniques, to maximize the energy efficiency of system wireless transmission by scheduling the system's resources while satisfying the transmission rate of the respective users. For MIMO-OFDM wireless communication systems in dynamic spectrum-aware environments, techniques such as deep stacking spike delay feedback reservoir computation can be used to exploit the spatial-temporal correlation characteristics of the environment and build new energy-efficient spectrum-aware schemes. In addition, M. Makhanbet et al. proposed a multi-objective power control algorithm to minimize the linear combination of system wireless transmission delay and energy consumption for uplink dynamic large-scale MIMO wireless communication systems, and an adaptive learning algorithm was proposed to learn the dynamic changes of the network environment to design delay- and energy-aware novel wireless transmission strategies.

In addition to the above-mentioned research on wireless transmission, researchers also combine wireless transmission with specific computing scenarios to study resource scheduling oriented to the integration of computing and communication, and optimize computing task transmission and offloading to support the completion of computing tasks. Specifically, for cloud computing networks, the correlation of computing tasks has a non-negligible impact on system performance, when dynamic offloading and collaborative scheduling methods of tasks can be designed based on wireless transmission to effectively reduce the delay of task computation and improve the corresponding energy efficiency. For content-centric fog access networks, a nonsmoothing optimization algorithm can be used to optimize the multicast beamforming of the system and design the corresponding wireless transmission scheme to maximize the energy efficiency of the system. For

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wirelessly charged heterogeneous fog-cloud computing networks, the maximum-minimum energy balance for multiple users can be obtained by jointly optimizing the system resources such as time, frequency of computing units, and computing mode. The researchers have also conducted preliminary research on the application of wireless transmission to edge computing and high-performance computing, and have achieved certain research results.

For edge computing networks, the researchers designed a new logical combination of performance metrics from transmission rate and energy consumption, and designed an opportunistic selection scheme for computing nodes based on branch switch-and-stay combining (SSC) technology, which effectively reduces the delay and energy consumption of transmission and task computing. In addition, for mobile edge computing networks in eavesdropping environment, the researchers design a new logical combination performance metric from the secure data rate and energy consumption of transmission, and analyze the resolution and asymptotic performance of the system, revealing the mechanism of the interaction between system delay and energy consumption in eavesdropping environment.

3. Challenges on High-EE wireless transmission

From the analysis of the above research status, we can find that researchers have made some progresses in the high-EE wireless transmission, which has promoted the development of wireless networks. However, there are still some challenges on high-EE wireless transmission. For example, how to enhance the system energy efficiently by using deep learning based methods still remains unsolved. In particular, the current framework is not intelligent, which can not be directly used in the future intelligent wireless communication systems. The second challenge is how to incorporate the energy efficiency with the federated learning, in order to achieve a distributed energy efficiency framework for future communication networks. Such challenges should be seriously addressed by the researchers from the fields of both wireless communication and mobile computing.

4. Feasible solutions to High-Energy efficiency wireless transmission

First, a new wireless transmission model and mechanism based on over-the-air computing is designed in terms of communication and computing performance. Consider an over-the-air computing-based wireless transmission system, as shown in Fig. 1, where each terminal device needs to upload its sensed environmental data to the edge server for information aggregation and exchange via a wireless link. Since the edge server

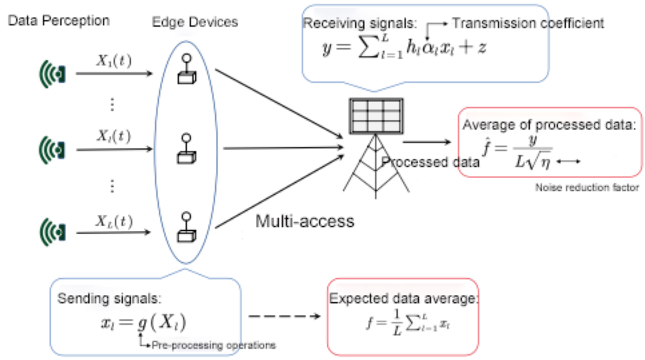

Figure 1. Air calculation schematic.

only needs the aggregated average data, the waveform superposition feature can be used to control the computation, i.e., decoding and receiving data averages directly during wireless transmission, which enables the integration of communication and computation, avoiding separate decoding of each user's data, significantly improving computational performance and reducing system overhead.

In this over-the-air computing system, consider that the edge server focuses only on the average of the information sent by all end devices. Specifically, let the model parameter of each end device be X_l, and then the objective of the edge server is to decode $\tilde{f} = \frac{1}{L}\left(\sum_{l\in\mathcal{L}} X_l\right)$. In the over-the-air computing, each end device first performs the normalization operation $g_l(\cdot)$ and sends the message $x_l \triangleq g_l(X_l)$, while the edge server detects the average value $f = \frac{1}{L}\sum_{l=1}^{L} x_1$ after receiving the signal, and then obtains the valid information $g_l(\cdot)$ by the denormalization operation $\tilde{f} = g_l^{-1}(f)$. How to recover f effectively is the focus of this part of the study.

Assume that the system has a constraint of T for latency and the end device l sends the information X_l to the edge server. Let h_l and α_l denote the channel and transmission coefficient from the end device to the edge server, respectively, and then the signal received by the edge server is $y = \sum_{l=1}^{L} h_l \alpha_l x_l + z$, where z is the noise. Let P_1 be the maximum transmission power of each terminal device, and then the terminal device receives a power constraint of $|a_l|^2 \leq P_l, \forall l \in \mathcal{L}$. Then, the processed information obtained by the edge server at this time is $\hat{f} = \frac{y}{L\sqrt{\eta}}$, where η is the noise reduction factor.

To effectively measure the link performance of over-the-air computing, computational mean square error and computational rate are the two main metrics. However, the computational mean square error metric is often used in the uncoded transmission scenario, while the computational rate relies on infinite code length coding to achieve zero computational error, so it is necessary to analyze the theoretical tradeoff

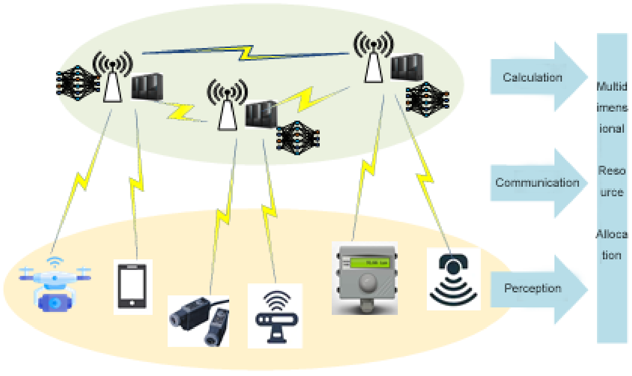

Figure 2. Multidimensional Resource allocation for edge intelligent networks.

between computational rate and computational mean square error and their effects on accuracy, speed, and energy consumption by combining information theory and signal processing theory. Further, a joint optimization scheme of transmit power allocation and receiver noise reduction for over-the-air computing is needed to improve the computation rate and reduce the computation mean square error and system energy consumption.

Secondly, we study the energy-efficient and high-spectrum-efficient transmission strategy with the linkage of multi-dimensional resources such as communication and computational sensing. From energy efficiency, end-to-end delay and task accuracy, the system performance metrics are established. For real-time decision-making application scenarios, the effectiveness of system decision depends on the timeliness of environment-aware data and the accuracy of environment-awareness. The energy efficiency of the system determines the stability of the system decision, which is also very important. Therefore, in this study, the end-to-end delay from the generation of sensed data to the target node to obtain the computation result and the accuracy of system decision, as well as the system effectiveness of this process, are used as objective metrics to measure the overall system performance.

The impact of multidimensional system resources such as communication and computational perception on system performance should be analyzed to establish a theoretical model between performance metrics and transmission-computation linkage system parameters. For environmental sensing data, let vector (Len, C, Len', v_i) characterize the sensing data itself, where Len denotes the size of the sensing data, C denotes the number of CPU revolutions required to compute the sensing data, Len' denotes the size of the sensing data computation result, and v_i denotes the value of the sensing data to node $i \in \mathcal{I}$. Let vector (t_i, w_i, e_i) characterize the performance metrics of the perceptual data, where t_i denotes the latency, w_i denotes the accuracy, and e_i is the system energy consumption. And the value of perceptual data to node $i \in \mathcal{I}$ can be defined as $v_i = -\lambda_1 t_i + \lambda_2 w_i$. The perceptual data latency includes data offloading latency, data computation processing latency, and computation result feedback latency, $t_i = t_{\text{off}} + t_{\text{com}} + t_{i,\text{tran}}$. Let $\alpha_{i,i'}$ denote whether the sensory data generated by sensory node $i \in \mathcal{I}$ is computed and processed at node $i' \in \mathcal{I}$or not, and $\beta_{i,i'}$ denote whether the computation result of the sensory data computed by node $i \in \mathcal{I}$ is sent to node $i' \in \mathcal{I}$ or not. Then, we can have [10–12],

$$\begin{aligned} t_{\text{off}} &= \sum_{i \in \mathcal{I}} \alpha_{i,i'} \,\text{Len}/r_{i,i'}, \\ t_{\text{com}} &= \sum_{i \in \mathcal{I}} \alpha_{i,i'} C/f_{i_1 i'}, \\ t_{i,\text{tran}} &= \sum_{i \in \mathcal{I}} \beta_{i,i'} Len'/r_{i,i'}, \end{aligned} \tag{1}$$

where $f_{i,i'}$ is the CPU frequency at which node $i \in \mathcal{I}$ computes data from node $i' \in \mathcal{I}$, and $r_{i,i'}$ is the transmission rate between node $i \in \mathcal{I}$ and node $i' \in \mathcal{I}$, which can be expressed as [13, 14]

$$r_{i,i'} = B_{i,i'} \log_2 \left(1 + \text{SNR}_{i,i'}\right), \tag{2}$$

where $B_{i,i'}$ and $\text{SNR}_{i,i'}$ are the channel bandwidth and signal-to-noise ratio between node $i \in \mathcal{I}$ and node $i' \in \mathcal{I}$, respectively. In addition to this, the system energy consumption e_i also consists of three components, namely, offloading energy consumption, computation energy consumption, and feedback energy consumption, i.e., $e_i = e_{\text{off}} + e_{\text{com}} + e_{i,\text{tran}}$, given by,

$$\begin{aligned} e_{\text{off}} &= t_{\text{off}} \times p_1, \\ e_{\text{com}} &= \textstyle\sum_{i \in \mathcal{I}, i' \in \mathcal{I}} \alpha_{i,i'} \eta C f_{i,i'}^2, \\ e_{i,\text{tran}} &= t_{i,\text{tran}} \times p_2, \end{aligned} \tag{3}$$

where η is the CPU energy consumption coefficient, P_1 is the offloading power, and P_2 is the feedback power.

Further, the optimal resource allocation strategy is studied for different system performance requirements. The optimal resource allocation of the group sensing network can be investigated by optimizing the sensing data sharing and computing strategies based on the differences in sensing data and communication and computing resources of terminal devices and edge services while satisfying different node performance metrics:

$$\begin{aligned}
\min_{(a_{i,k},\beta_{i,k},B_{i,k},L,C)} &\rho_1 \sum_{i\in\mathcal{I}} t_1 + \rho_2 \sum_{i\in\mathcal{I}} e_i \\
\text{s.t.} &\sum_{i'\in\mathcal{I}} \beta_{i,i'} v_i \geq V_{i,\min}, \\
&\sum_{i\in\mathcal{I}} f_{i,i'} \leq f_{i',\max}, \\
&\sum_{i\in\mathcal{I}} B_{i,i'} \leq B_{i',\max},
\end{aligned} \tag{4}$$

where $B_{i,\max}$ is the available bandwidth of node $i \in \mathcal{I}$, ρ_1 and ρ_2 are the weighting factors, $f_{i',\max}$ is the maximum computation rate of node $i' \in \mathcal{I}$, and $V_{i,\min}$ is the minimum data value required by node $i \in \mathcal{I}$.

By solving the above problems, the optimal resource deployment for a given system performance metric can be obtained, and then the intrinsic relationship between the system performance and resource allocation can be obtained. At the same time, optimization methods such as convex and nonconvex optimization are used to design task-aware and computational offloading strategies for dynamic scenarios to optimize the overall network performance for both offline and online system scenarios.

5. Conclusions

With the deployment and commercialization of 5G mobile communication networks, the access nodes and data volume of wireless networks are showing massive and explosive growth. In this paper, we firstly reviewed the research progress on the energy-efficient and spectrum-efficient wireless transmission, from the perspectives of both latency and energy consumption. We then provided several solutions to high-efficiency wireless transmission for the 5G wireless networks. Finally, we gave some discussions about the future road for the design of energy-efficient and spectrum-efficient wireless transmission, which provides some theoretical reference for the system design of wireless networks and IoT networks.

5.1. Data Availability Statement

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5.3. Copyright

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