# Resource Allocation for Near-Field Communications: Fundamentals, Tools, and Outlooks

Bokai Xu, Jiayi Zhang, Senior Member, IEEE, Hongyang Du, Zhe Wang, Yuanwei Liu, Senior Member, IEEE, Dusit Niyato, Fellow, IEEE, Bo Ai, Fellow, IEEE, and Khaled B. Letaief, Fellow, IEEE

Abstract—Extremely large-scale multiple-input-multipleoutput (XL-MIMO) is a promising technology to achieve high spectral efficiency (SE) and energy efficiency (EE) in future wireless systems. The larger array aperture of XL-MIMO makes communication scenarios closer to the near-field region. Therefore, near-field resource allocation is essential in realizing the above key performance indicators (KPIs). Moreover, the overall performance of XL-MIMO systems heavily depends on the channel characteristics of the selected users, eliminating interference between users through beamforming, power control, etc. The above resource allocation issue constitutes a complex joint multi-objective optimization problem since many variables and parameters must be optimized, including the spatial degree of freedom, rate, power allocation, and transmission technique. In this article, we review the basic properties of near-field communications and focus on the corresponding "resource allocation" problems. First, we identify available resources near-field communication systems and highlight their distinctions from far-field communications. Then, we summarize optimization tools, such as numerical techniques and machine learning methods, for addressing near-field resource allocation, emphasizing their strengths and limitations. Finally, several important research directions of near-field communications are pointed out for further investigation.

Index Terms—Near-field communications, XL-MIMO, resource allocation, optimization algorithm, machine learning.

## I. INTRODUCTION

With the advent of next-generation wireless networks beyond fifth generation (B5G) and sixth generation (6G), performance requirements will become increasingly stringent, including unprecedented data rates, high reliability, global coverage, and ultradense connectivity. Various physical antennas such as holographic multiple-input-multiple-output (MIMO), intelligent reflecting surfaces (IRS), and very large scale antennas, as well as millimeter wave, ultra-dense networks, and other new technologies, can make the above possible. Among numerous 6G technologies, the extremely large-scale MIMO (XL-MIMO) can provide high spectral efficiency (SE), high energy efficiency (EE), and reliable massive access [1], [2]. Moreover, it has evolved far-field communications into near-field communications. To further optimize system performance, improve user experience, reduce energy consumption,

B. Xu, J. Zhang, Z. Wang and B. Ai are with Beijing Jiaotong University; H. Du, and D. Niyato are with Nanyang Technological University; Y. Liu is with Queen Mary University of London; K. B. Letaief is with Hong Kong University of Science and Technology.

and enhance anti-interference capability, radio resource allocation has become a core component in wireless communication networks. Additionally, due to the diversity and complexity of application scenarios and wireless environment, near-field communications resource allocation is also facing significant challenges.

In contrast to traditional far-field assumptions, 6G will have a technical trend toward higher frequency migration and active/passive antenna deployment, which is expected to have fundamentally different electromagnetic propagation. Specifically, large aperture arrays may result in a Rayleigh distance exceeding the transmission distance [3]. Increasing the aperture of the antenna results in scatterers and users being located in the near-filed region of the antenna array. In general, near-field channels have the following typical characteristics:

- Near-field Spherical Wave Properties: Spherical wavefronts are more accurate at describing phase differences in the near-field. Furthermore, due to the beam focusing capabilities of near-field transmissions, we can reliably communicate with multiple users in the same angular direction at different distances, which is impossible with conventional far-field beam steering [3].
- *Near-field Non-stationary Properties:* Additionally, the large aperture has the non-stationarity property of only receiving signals from a relatively small area known as the visibility region (VR) in different parts of the array [4], [5].
- Near-field Electromagnetic Properties: Compared with traditional far-field massive MIMO communications, electromagnetic waves will gain new polarization flexibility and degree of freedom, and the mutual coupling effect between antennas will be intensified.

Based on the above characteristics of the near-field channel, there are many resources to be allocated, including power control, beamforming, antenna selection, user scheduling, and channel estimation, mechanisms of which are different from far-field. The SE, EE, bit error rates (BER), user fairness, and quality-of-service (QoS) are common matrics for assessing far-field communications performance. Near-field communications not only improve performance in the above metrics but also bring new metrics such as mutual information, effective degrees of freedom (EDoF), and beam depth (BD), etc. Near-field communications have different optimization objectives and constraints due to differences in resource allocation issues and evaluation metrics. Consequently, corresponding optimization tools and methods need to be considered. In

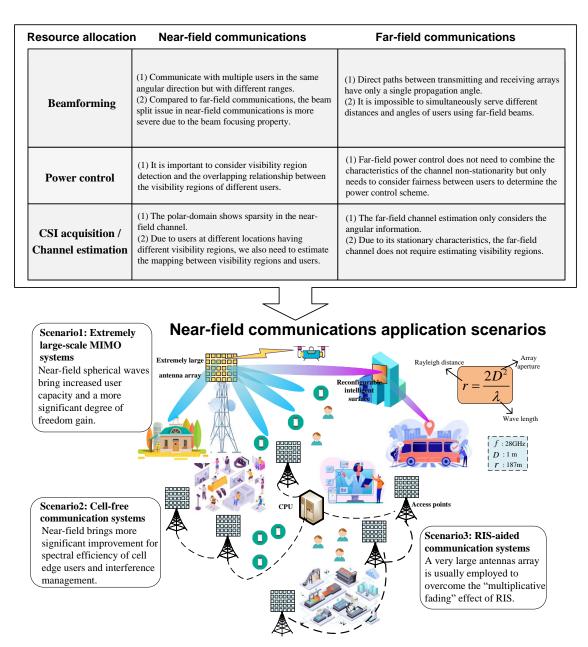


Fig. 1: The major differences in resource allocation between near and far-field include beamforming, power control, and channel estimation. We consider a communication system with a frequency of 28GHz and an array aperture of 1m. Accordingly, the Rayleigh distance is 187m, and users are more likely located in the near-field region. The major application scenarios for near-field resource allocation include XL-MIMO systems, RIS-aided communication systems, and cell-free communication systems.

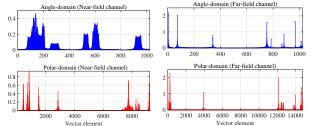
Fig. 1, we illustrate some typical applications of near-field communications for improving the performance of wireless systems and compare resources in near-field and far-field.

Due to the new characteristics of near-field communications, specifically for XL-MIMO, traditional far-field resource allocation schemes are no longer applicable. At the same time, many new antenna structures and signal processing architectures were introduced, so the optimization algorithms needed to be redesigned. To fully utilize near-field resources, joint optimization designs are often required, making the optimization solution extremely difficult and often unable to obtain

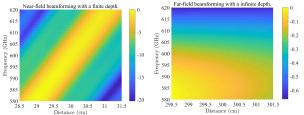
a closed form solution. Therefore, a typical approach for highdimensional joint resource design problems is to transform non-convex optimization problems into convex optimization problems and then introduce algorithms such as alternating optimization, deep reinforcement learning (DRL), and other optimization tools to solve them.

With the focus on near-field resource allocation, the main contributions of this paper can be summarized as follows:

• We discuss the channel characteristics of near-field communications. We also elucidate the disparities between nearfield and far-field resource allocation. Furthermore, we explore



(a) Polar- and angle-domain channel vectors in the near-field and far-field. For the near-field channel, it has better sparsity in the polar-domain than in the angle-domain.



(b) The focus point changes with the frequency. Conventional far-field beam from a specific distance continues toward infinity, while near-field beam has a finite depth around the focal point.

Fig. 2: Comparison of near-field and far-field channel characteristics.

the challenges associated with resource allocation in near-field communications and propose possible solutions.

- We review approaches for near-field resource allocation. The major optimization tools include traditional numerical optimization, heuristic optimization, and machine learning (ML) optimization. We then present the process of solving general near-field resource allocation problems, highlighting the strengths and limitations between traditional numerical optimization algorithms and ML algorithms. Moreover, the characteristics of the algorithm and the types of problems that each optimization tool can handle are revealed.
- We simulate and compare traditional optimization algorithms with ML algorithms. Our investigated solutions can serve as a novel framework for near-field modeling and performance optimization. Finally, important research directions are highlighted for further studies.

## II. CHARACTERISTICS OF NEAR-FIELD COMMUNICATIONS

In this section, we present new properties of near-field communications, encompassing non-stationarity, spherical beam focusing, and electromagnetic characteristics. We then introduce the near-field resource allocation framework. Furthermore, we propose the main challenges and possible solutions to improve the performance of near-field resource allocation utilizing near-field characteristics.

## A. Near-field Non-stationary Properties

XL-MIMO near-field communications exhibit a characteristic of non-stationarity. Different parts of the array can observe distinct terminals when the array size becomes very large since the energy of every terminal is focused on a specific area of the array. Due to the limited channel power of outside antennas,

the VR-based channel model allows radio frequency (RF) chains to assign VR to each user dynamically. Consequently, a dynamic architecture with low complexity could provide a similar level of performance as a fully digital system, but at a lower hardware cost. This makes it possible to reduce the number of RF chains and signal processing units to reduce power consumption and improve SE by scheduling users in different VRs. A major challenge for near-field resource allocation caused by the non-stationary properties is *how to carry out user scheduling and antenna selection to improve SE and EE in non-stationary channels?* 

# B. Near-field Spherical Wave Properties

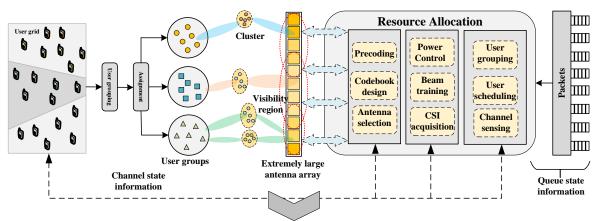
As the electromagnetic wave propagation model changes from far-field plane wave to near-field spherical wave, multiple propagation angles are available between the transceiver array, which can support parallel transmission of multi-stream data and significantly improve the gain of degrees of freedom. As shown in Fig. 2, the spherical wave propagation in near-field enables beam focusing in the polar-domain. By exploiting this property, the beam can be focused at a specific angle and at a specific distance. Moreover, the far-field channel is sparse in the angle-domain, but suffers energy leakage in the polar-domain. The near-field channel has better sparsity in the polar-domain than in the angle-domain. Regarding the near-field spherical wave property, the challenge lies in *how can beamforming improve SE*, *EE*, and EDoF under the near-field spherical wave?

## C. Near-field Electromagnetic Properties

Another new feature of near-field communications is the introduction of electromagnetic properties due to the change in the aperture of the antenna array. When the aperture of a linear array tends to be spatially continuous, i.e., holographic MIMO, the propagation mode, polarization, and spatial freedom of the electromagnetic wave in space will bring about great differences. In contrast to far-field communications, the influence of antennas on the wireless channel propagation environment is further amplified. Consequently, it becomes imperative to incorporate microwave network theory, impedance matching networks, and other methodologies to jointly model antennas and propagation channels. In addition, the compact antenna array has more sampling points in space and can capture more wavenumber domain information. By utilizing this mechanism, spatial electromagnetic waves can be exploited to achieve extreme spatial resolution and high SE. Therefore, another major challenge of near-field communications arising from these unique electromagnetic properties is how to construct channel models for the free-space propagation environment (LoS) and the arbitrary scattered propagation environment (NLoS) scenarios? In addition, we need to design corresponding beamforming techniques to reach the fundamental limits with an acceptable complexity based on the above channel models.

In Fig. 3, we summarize the framework for near-field resource allocation and propose three challenges and possible solutions.

## Framework of near-field resource allocation



# Characteristics of near-field channels, challenges, solutions for resource allocation

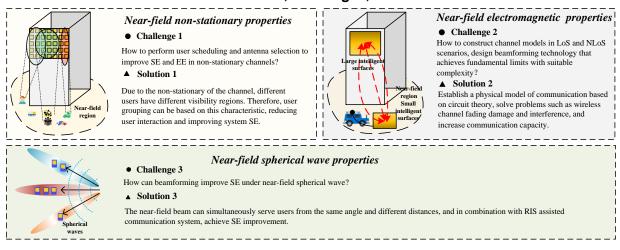


Fig. 3: At the base station, the signal arrives at the receiver through resource allocation strategies such as precoding and power control, passing through the near-field channel. At the receiver, user grouping and scheduling strategies improve efficiency. Besides, we introduce three major challenges and solutions for near-field resource allocation.

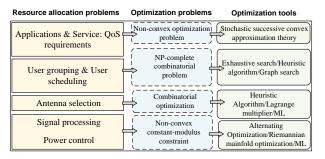


Fig. 4: Near-field resource allocation problems and corresponding optimization problems and tools.

# III. OPTIMIZATION TOOLS FOR RESOURCE ALLOCATION IN NEAR-FIELD COMMUNICATIONS

In this section, we delve into optimization tools for near-field resource allocation and classify them into three distinct categories: numerical optimization based methods, heuristic optimization based methods, and ML based methods. Subsequently, we explore the optimization problems to which these

algorithms can be applied, examine resource allocation scenarios, and analyze the key characteristics of these algorithms. In Fig. 4, we summarize the near-field resource allocation problems and corresponding suitable optimization methods.

## A. Numerical Optimization based Approach

Due to its reliability, versatility, and solid mathematical foundation, traditional numerical optimization algorithms become valuable tools for solving resource allocation problems and have found widespread applications in telecommunications [14]. Due to the unique nature of resource allocation problems and the diverse structures of antenna arrays, new optimization problems have to be formulated. Depending on the specific forms of the objectives and constraints, one can select appropriate numerical optimization tools to address them.

1) Alternating Optimization: One type of alternating optimization is the Alternating Minimization (AM) algorithm, commonly used in collaborative filtering and matrix factorization problems. In contrast to the traditional far-field beam

TABLE I: The optimization tools for near-field resource allocation and solutions include numerical optimization, heuristic optimization, and machine learning.

Opimization algorithm	Problem type	Beamforming /Combining /Power control	Codebook design	Antenna Selection	Beam training	User grouping /Scheduling	Sensing
Numerical Optimization based Approach							
Alternating optimization	Combinatorial optimization	[3], [6]	[7]	_	[7]	-	[8]
Riemannian manifold optimization	Non-convex constant-modulus constraint	[3]	[7]	-	[7]	-	-
Search algorithm	MINLP /NP-complete	[2], [5]	-	-	-	[4], [9]	-
Lagrange multiplier /SDR method	QCQP	[10]	-	[10]	-	-	[8]
Heuristic optimization based Approach							
Genetic algorithm	Combinatorial optimization	[10]	-	[10]	-	-	_
Machine Learning based Approach							
Deep learning	Linear inverse problems	-	[11]	_	[11]	-	_
Reinforcement learning (DDPG)	Discrete optimization	_	[12]	-	-	_	-
Multi-agent Reinforcement learning (MADDPG)	Discrete optimization	[13]	-	[13]	_	-	_

steering that can only point in a specific direction, the near-field spherical wave propagation brings the possibility of focusing the beam at a particular position. Furthermore, near-field beamforming can be transformed into a combinatorial optimization problem and solved using the AM algorithm [6]. According to [3], the authors proposed an alternating design algorithm to jointly optimize the dynamic metasurface antennas (DMAs) configuration and beamforming, i.e., configurable weights of the DMAs are optimized first, and digital precoding vectors are later. Additionally, beam focusing based on the proposed algorithms can achieve notable gains in SE compared to designs assuming conventional far-field operation. More significantly, it is shown that the SE of DMAs is comparable to that of fully digital architectures.

- 2) Riemannian manifold: Optimization over a Riemannian manifold is locally analogous to optimization over the Euclidean space with smooth constraints. Therefore, a well-developed conjugate gradient algorithm in Euclidean spaces can also be applied to Riemannian manifolds. Compared with far-field beam training, near-field beam training needs to search for angle parameters and additional distance-related factors to accurately focus the beam, which leads to excessive training overhead and computational complexity. The authors in [7] modeled it as a combinatorial optimization problem with non-convex constraints in constant mode and applied the manifold optimization method to solve it. Despite slight beamforming performance degradation, training overhead can be reduced by over 99% compared with the bottom-layer overall codewords exhaustive searching.
- 3) Search Algorithm: Near-field resource allocation search schemes include greedy search, graph search, graph matching, etc. For instance, the authors in [9] designed an efficient greedy algorithm to solve mixed integer non-convex optimization problems in near-field user grouping and antenna selection. Although this algorithm has high complexity, it can

significantly improve system spectral efficiency when users are densely distributed. Moreover, an adjustable RF chain beamforming structure was proposed in [2] to fully utilize the additional spatial degrees of freedom introduced by the near-field spherical wave to enhance the capacity of a single-user system. In addition, they proposed a low-complexity algorithm to optimize the selection matrix, which approximates exhaustive searching.

4) Other Approaches: We illustrate additional optimization algorithms employed in near-field resource allocation. Nearfield communications use a high degree of freedom and spherical wave introduced by the very large scale antenna to meet various OoS requirements of users and maintain their fairness. The problem is usually modeled as a nonconvex joint high-dimensional resource optimization problem, which cannot be solved by traditional convex optimization methods. However, the problem can be transformed into a convex optimization problem by stochastic successive convex approximation theory, and then solved by using existing convex optimization tools. Additionally, there are combinatorial optimization problems related to near-field resource allocation, such as quadratically constrained quadratic program (QCQP) problems. Due to the large antenna array size, traditional semidefinite relaxation (SDR) optimization methods require an enormous computation burden, which is no longer applicable. Therefore, this necessitates low-complexity strategies, such as the constrained least square (LS) method or ML optimization tools.

### B. Heuristic Optimization based Approach

Heuristic optimization-based methods cover a variety of algorithms for solving complex non-convex and combinatorial optimization problems. One widely adopted metaheuristic approach for solving the resource allocation problem in antenna

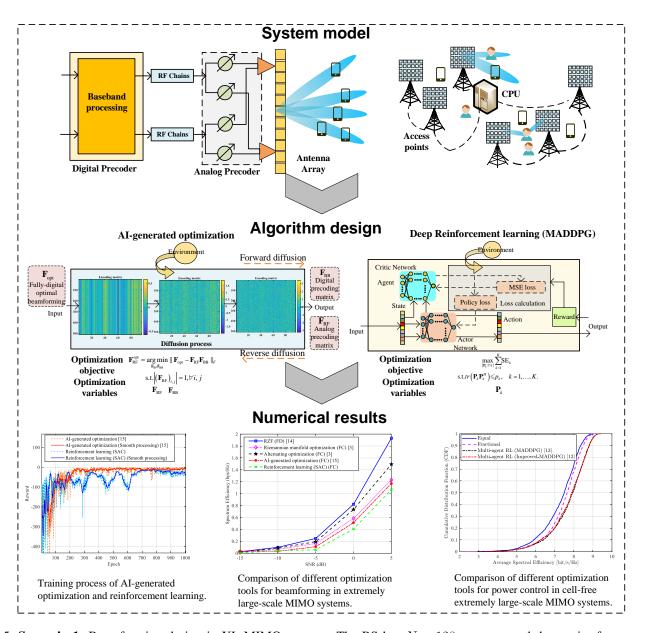


Fig. 5: **Scenario 1:** Beamforming design in XL-MIMO systems. The BS has N=128 antennas and the carrier frequency is f=30 GHz. **Scenario 2:** Power control in cell-free communication systems. The number of access points is 9, serving 6 receivers. The communication bandwidth is 20 MHz and the noise power is  $\sigma^2=-69$  dBm. All transmitters transmit with a transmission power of no more than 200 mW.

selection is the Genetic Algorithms (GA). This technique incorporates multiple search phases to effectively explore the feasible solution space and exploit the favorable properties of candidate solutions, aiming to identify promising regions within the feasible subspaces. Unlike exact optimization methods, GA does not require convex objective functions or constraints. Moreover, the computational complexity can be adjusted to match the available computational resources by tuning the input parameters and the number of iterations. However, it should be noted that, similar to other metaheuristics, GA does not guarantee to find the optimal solution [10]. GA is also not good with problems with constraints, and it may converge very slowly.

## C. Machine Learning based Approach

ML has emerged as one of the most dynamic areas in contemporary signal processing. In contrast to the traditional iterative methods, where an algorithm is executed over multiple iterations, the concept of deep unfolding represents these iterations as a sequence of identical processing layers.

• Deep learning based approach: Compared to far-field channels, the near-field channel does not exhibit sparsity in the angle domain but exhibits sparsity in the polarization domain. Therefore, codebook design must consider both the angle and distance between the transmitter and the receiver, which differs from the far-field domain. The authors in [11] proposed a deep learning-based beam training technique using two neural

networks to estimate the optimal angle and distance for near-field beams. Moreover, the improved scheme can increase effective achievable rates and reduce the pilot overhead by approximately 95% compared to the beam sweeping technique.

• Deep reinforcement learning based approach: For highdimensional resource allocation problems such as time, space, frequency, and degree of freedom in near-field, traditional numerical optimization algorithms often cannot solve this kind of joint optimization design problem. The joint design method based on reinforcement learning algorithm can dynamically adjust its own decision-making strategy through the interaction between the agent and the environment, and obtain the optimal expected reward. The authors in [12] proposed a framework to optimize the codebook beam patterns based on the environment. Furthermore, the proposed solution produces beams with similar SNR and approaches ideal beam shapes. For nearfield antenna selection and power control problems, singleagent reinforcement learning is no longer suitable for such complex scenarios when the user has mobility or is served by multiple base stations. In contrast, multi-agent reinforcement learning performs better in this combinatorial optimization problem [13]. Moreover, it can reduce CSI interaction, reduce complexity and improve energy efficiency by using part of information to exchange and share information among users.

To sum up, we present a list of main resource allocation problems and optimization tools in Table I for ease of reference.

# IV. USE CASES

This section evaluates and demonstrates near-field resource allocation designs and optimization. We consider two scenarios for near-field resource allocation: XL-MIMO and cell-free communication systems.

Scenario 1: We consider a fully-digital and hybrid fullyconnected precoded architecture, the number of RF chains and the number of receivers are 4. For performance comparison of beamforming schemes, we consider the three traditional numerical optimization algorithms: Optimal beamforming [14], Riemannian manifold optimization, alternating optimization [3] and reinforcement learning. Moreover, we compare a generative AI-based method, called AI-generated optimization, whose key technology is generative diffusion models [15]. Through a process known as forward diffusion, the generative diffusion model gradually adds Gaussian noise over time, generating targets for the training process of a denoising neural network. From Fig. 5, we can observe a trade-off between the performance and complexity of the algorithms: although traditional Riemannian optimization and alternating optimization can both approach the optimal solution, these two algorithms require more iterations. Furthermore, the above near-field beamforming schemes can reliably communicate with multiple users in the same angular direction but with different ranges, which is impossible in far-field beam steering. In addition, if the receivers have high mobility, i.e., the channel is constantly changing, the two methods require recalculation at every moment, which is extremely time-consuming. Alternately, AI-generated optimization is more suitable for

complex and ever-changing scenarios. However, performance is slightly reduced. Moreover, AI-generated optimization is superior to the reinforcement learning algorithm, e.g., Soft Actor Criticism (SAC), which has faster convergence and better performance.

Scenario 2: As shown in Fig. 5, we consider the nearfield power control scenario of multiple base stations. It is observed that the multi-agent reinforcement learning (MAD-*DPG*) [13] is better than the traditional power control scheme. Due to the high dimensionality of the near-field array and the mobility of users, traditional power allocation schemes applied in the far-field cannot be applied. On the contrary, using MADDPG to utilize decisions between multiple agents can better solve complex optimization problems in the nearfield. Moreover, the training time of MADDPG and Improved-MADDPG algorithms is 0.554 s and 0.610 s respectively, and the convergence time is 178 s and 75 s respectively. Furthermore, the Improved-MADDPG algorithm can significantly improve the convergence speed of the MADDPG problem, and compared to traditional optimization algorithms, multiagent deep reinforcement learning algorithms can significantly reduce interference between antennas and achieve better power control performance.

### V. CONCLUSIONS AND FUTURE DIRECTIONS

In this article, we provided a comprehensive overview of near-field resource allocation for XL-MIMO systems. Specifically, we first presented near-field channel characteristics. For near-field optimization problems, we presented a solution framework and optimization tools. Additionally, we explained which kinds of resource allocation problems that are suitable for numerical, heuristics, and ML. Some other directions for future research in near-field communications are outlined as follows.

Electromagnetic information theory: Electromagnetic information theory is a promising direction, based on extremely large antenna array (ELAA) technology and holographic massive MIMO technology, to consider how to surpass the classic Massive MIMO problem. Nevertheless, this introduces high-dimensional channels, space, degrees of freedom, and other resources in the near-field and makes channel modelling, network deployment, and scheduling users more challenging. In future electromagnetic information theory research, how to allocate the resources above in the near-field will be crucial.

Semantic Communications: Semantic communication is considered a breakthrough beyond the Shannon paradigm, to transmit the semantic information the source conveys successfully. Near-field communications that use semantic communication compress or encode the original data instead of sending it, thus reducing the amount of data needed to be transmitted while requiring less bandwidth and energy. Furthermore, near-field resource allocation enables a greater spatial degree of freedom and SE, which can accommodate new wireless communication applications requiring larger capacity.

## REFERENCES

Z. Wang, J. Zhang, H. Du, D. Niyato, S. Cui, B. Ai, M. Debbah,
 K. B. Letaief, and H. V. Poor, "A tutorial on extremely large-scale

- MIMO for 6G: Fundamentals, signal processing, and applications," arXiv:2307.07340, 2023.
- [2] Z. Wu, M. Cui, Z. Zhang, and L. Dai, "Distance-aware precoding for near-field capacity improvement in XL-MIMO," in *Proc.* 2022 IEEE 95th Veh. Technol. Conf. (VTC Spring), Jun. 2022, pp. 1–5.
- [3] H. Zhang, N. Shlezinger, F. Guidi, D. Dardari, M. F. Imani, and Y. C. Eldar, "Beam focusing for near-field multiuser MIMO communications," *IEEE Trans. Wireless Commun.*, vol. 21, no. 9, pp. 7476–7490, Sep. 2022.
- [4] J. H. I. de Souza, J. C. M. Filho, A. Amiri, and T. Abrão, "QoS-Aware user scheduling in crowded XL-MIMO systems under non-stationary multi-state LoS/NLoS channels," *IEEE Trans. Veh. Technol.*, vol. 72, no. 6, pp. 7639–7652, Jun. 2023.
- [5] K. Zhi, C. Pan, H. Ren, K. K. Chai, C.-X. Wang, R. Schober, and X. You, "Performance analysis and low-complexity design for XL-MIMO with near-field spatial non-stationarities," *arXiv:2304.00172*, 2023.
- [6] Z. Wang, X. Mu, and Y. Liu, "Beamfocusing optimization for near-field wideband multi-user communications," arXiv:2306.16861, 2023.
- [7] X. Shi, J. Wang, Z. Sun, and J. Song, "Spatial-chirp codebook-based hierarchical beam training for extremely large-scale massive MIMO," *IEEE Trans. Wireless Commun.*, pp. 1–1, to appear, 2023.
- [8] Z. Wang, X. Mu, and Y. Liu, "Near-field integrated sensing and communications," *IEEE Commun. Lett.*, vol. 27, no. 8, pp. 2048–2052, May 2023
- [9] X. Li, Z. Dong, Y. Zeng, S. Jin, and R. Zhang, "Multi-user modular XL-MIMO communications: Near-field beam focusing pattern and user grouping," arXiv:2308.11289, 2023.
- [10] J. a. H. I. de Souza, A. Amiri, T. Abrão, E. de Carvalho, and P. Popovski, "Quasi-distributed antenna selection for spectral efficiency maximization in subarray switching XL-MIMO systems," *IEEE Trans. Veh. Technol.*, vol. 70, no. 7, pp. 6713–6725, May 2021.
- [11] W. Liu, H. Ren, C. Pan, and J. Wang, "Deep learning based beam training for extremely large-scale massive MIMO in near-field domain," *IEEE Commun. Lett.*, vol. 27, no. 1, pp. 170–174, Jan. 2023.
- [12] Y. Zhang, M. Alrabeiah, and A. Alkhateeb, "Reinforcement learning of beam codebooks in millimeter wave and terahertz MIMO systems," *IEEE Trans. Commun.*, vol. 70, no. 2, pp. 904–919, Feb. 2022.
- [13] Z. Liu, J. Zhang, Z. Liu, H. Du, Z. Wang, D. Niyato, M. Guizani, and B. Ai, "Cell-free XL-MIMO meets multi-agent reinforcement learning: Architectures, challenges, and future directions," arXiv:2307.02827, 2023
- [14] E. Björnson, M. Bengtsson, and B. Ottersten, "Optimal multiuser transmit beamforming: A difficult problem with a simple solution structure [lecture notes]," *IEEE Signal Process. Mag.*, vol. 31, no. 4, pp. 142–148, Jul. 2014.
- [15] H. Du, R. Zhang, Y. Liu, J. Wang, Y. Lin, Z. Li, D. Niyato, J. Kang, Z. Xiong, S. Cui, B. Ai, H. Zhou, and D. I. Kim, "Beyond deep reinforcement learning: A tutorial on generative diffusion models in network optimization," arXiv:2308.05384, 2023.