Efficient Task Offloading for Multi-Access Edge Computing via Intelligent Reflecting Surface

Junhui Du, Huaming Wu, *Senior Member, IEEE*, Anwer Al-Dulaimi, and Shahid Mumtaz, *Senior Member, IEEE*

***Abstract*—With the widespread and rapid deployment of big data services and technologies like the Internet of Things (IoT) and 5G Advanced, users have become accustomed to applications that demand higher energy consumption and lower latency. As a result, alleviating the computing and communication burdens on user devices, while also addressing concerns related to cost and complexity, has become a major challenge. To tackle these challenges, this paper studies the task offloading problem in Intelligent Reflecting Surface (IRS)-assisted Multi-Access Edge Computing (MEC) networks in different scenarios, aiming to enhance the synergy between IRS and MEC. Firstly, we introduce an IRS-assisted MEC network. Secondly, we propose several optimization models for the IRS phase shift coefficient matrix. Finally, we highlight the advantages of the IRS in enhancing MEC communication through a simple experiment.**

***Index Terms*—Multi-Access Edge Computing, Intelligent Reflecting Surface, Task Offloading, Optimization Methods.**

I. Introduction

The rapid deployment of technologies such as the Internet of Things (IoT) and the Fifth-Generation Advanced (5G Advanced) wireless communication has led to increased performance and capacity demands on wireless communication systems. These demands are poised to become even more stringent with the advent of next-generation telecommunication networks like 6G. Mobile Devices (MDs) also impose strict requirements on computational complexity and latency. A common approach to meet these demands is to offload compute-intensive tasks from MDs to cloud servers with sufficient computing resources. However, the aforementioned approach may suffer from the drawback of high latency, as cloud servers are frequently situated at a considerable distance from MDs. In response to this challenge, Mobile Edge Computing (MEC) has emerged as a crucial technology to mitigate latency concerns. MEC allows the deployment of computing and storage resources in close proximity to the MDs, minimizing the delays associated with data exchanges. In order to further enhance the communication performance of MEC systems, several innovative technologies have emerged in the field of wireless communication in recent years. These include Backscatter Communication (BC), massive Multiple-Input Multiple-Output (MIMO), and Amplified Forward (AF) relay-assisted communication. While these technologies can significantly boost wireless system performance, they often come with high hardware costs and/or increased energy consumption. In contrast, Intelligent Reflecting Surfaces (IRS) have emerged as a promising and cost-effective solution, offering a way to enhance MEC system performance without the heavy reliance on expensive hardware or high energy demands.

Junhui Du and Huaming Wu are with the Center for Applied Mathematics, Tianjin University, Tianjin 300072, China. (e-mail: {dujunhui_0325, whming}@tju.edu.cn).

Anwer Al-Dulaimi is with the College of Technological Innovation, Zayed University, Abu Dhabi, UAE. (e-mail: anwer.aldulaimi@ieee.org).

Shahid Mumtaz is with the Department of Engineering, Nottingham Trent University, NG1 4FQ Nottingham, U.K. (e-mail: dr.shahid.mumtaz@ieee.org).

(Corresponding Author: Huaming Wu)

IRS is a technology that uses artificially manufactured surfaces to control the propagation of electromagnetic waves [1]. Typically, an IRS comprises a planar antenna array composed of a large number of low-cost passive reflecting elements. These elements can intelligently adjust the amplitude, phase, frequency, and polarization of incoming signals in real-time. By doing so, the signal is reflected toward a designated receiver, boosting its strength while also reducing interference. Through careful design and tuning of its components, IRS enables precise control over the transmitted signal, optimizing its quality and efficiency. Additionally, the IRS can dynamically reconfigure the channel environment, adapting to changing conditions in real-time.

We mainly studied the use of IRS in MEC networks to improve communication performance. The efficiency of task offloading can be significantly improved by enhancing the communication performance of MEC networks. Common task offloading methods include binary offloading and partial offloading. In traditional MEC scenarios, the external communication environment is generally passive, meaning the task offloading strategy can only be optimized based on the available external communication state. To address this, many studies have integrated IRS into MEC frameworks to improve the efficiency of task offloading [2]. Specifically, this paper encompasses two main aspects:

- Investigating IRS-assisted MEC networks across a variety of scenarios to uncover the potential benefits and applications of integrating IRS within the MEC framework. This research aims to identify how IRS can enhance the MEC system performance, scalability, and energy efficiency in different environments.
- Developing and exploring various optimization models for IRS phase shift coefficients to achieve optimal configuration and improve communication performance.

II. Background

A. Communication-Enhancing Technologies

We compare IRS to several other communication-enhancing technologies, namely, MIMO, BC and AF, highlighting its distinctive features and benefits, as shown in Table I.

TABLE I: Comparison of different communication technologies

Technologies	Principle	Advantages	Disadvantages	Typical Use Cases
IRS	Dynamic regulation of electromagnetic wave phase/amplitude; Reconfigurable channel	Low power consumption, low noise accumulation, flexible deployment, low cost, and strong scalability	Dependent on reflection conditions, requires real-time optimization via intelligent algorithms	Smart city coverage, IIoT, vehicular networks
MIMO	Base station equipped with tens to hundreds of antennas for spatial multiplexing	High spectral efficiency, high capacity, strong interference resistance	High power consumption, complex hardware, costly, requires dense base station deployment	5G macro cells, stadium high-density communication
AF	Relay nodes receive and amplify signals (may introduce noise)	Simple implementation, significant coverage extension	Noise amplification, low energy efficiency, requires external power supply	Remote area communication, emergency networks
BC	Passive devices reflect ambient signals and modulate information (e.g., RFID)	Extremely low power (battery-free), ultra-low cost, miniaturization	Short communication range ($\leq$10m), very low data rate, relies on external RF source	RFID tags, sensor networks

- **MIMO**: This refers to technology deployed on a large scale at both the transmitting and receiving ends. MIMO base stations require hundreds of antennas and RF chains, making them more than 10 times more expensive than IRS. In terms of power consumption, typical base stations can consume power in the kilowatt range. While MIMO technology significantly improves communication performance, it comes with substantial energy consumption and computational complexity, particularly in beamforming. For instance, in a concert setup, thousands of concurrent connections can be supported [3].
- **AF**: This refers to technology that enhances the signal during transmission before being sent to the receiver. On one hand, AF relays amplify both the signal and the noise, resulting in a decrease in the signal-to-noise ratio (SNR) by more than 3 dB; on the other hand, AF relays require a continuous power supply, making them significantly less energy-efficient than IRS. For instance, AF relay networks have been rapidly deployed in earthquake zones for recovery purposes [4].
- **BC**: This method involves the transmitter modulating its own signal onto a surrounding BS or access point, which is then transmitted to the receiver. While this approach saves energy at the transmitter, it introduces challenges related to signal interference. The communication distance for BC systems is typically less than 10 meters, with data rates generally limited to the kilobit-per-second range. BC systems also rely on an external RF source, such as a Wi-Fi router. One example is a medical implant that transmits temperature data via BC [5].
- **IRS**: In contrast to the aforementioned technologies, IRS not only proves to be more cost-effective but also mitigates energy consumption without introducing additional signal interference. Unlike traditional approaches to communication enhancement that primarily optimize parameters at the transmitter and receiver ends, IRS distinguishes itself by reconfiguring the communication environment to boost overall communication performance. However, IRS relies on ambient reflection conditions and increases the optimization complexity, requiring real-time optimization of the phase shift of IRS [1].

B. Advantages of Combining IRS and MEC

The combination of IRS and MEC offers several advantages:

- **Low Delay**: IRS can dynamically optimize wireless channels, reducing signal transmission path loss and mitigating multipath interference, which in turn enhances the communication quality between edge devices and MEC nodes (e.g., reducing packet loss and improving the SNR). In the MEC framework, data is processed close to the terminal, eliminating cloud round-trip delays. Together, these two technologies effectively minimize end-to-end latency: IRS optimizes physical layer transmission, while MEC reduces computational latency.
- **High Energy Efficiency**: IRS can reduce the transmitting power of the BS through passive reflection. In MEC, data tasks that cannot be processed locally are offloaded to the cloud for processing. Together, these technologies maximize energy efficiency by jointly optimizing IRS reflection parameters and MEC task offloading strategies, achieving a balanced "communication-computing" energy efficiency.
- **Capacity Expansion**: IRS enhances MEC service accessibility by extending the edge network to cover blind spots (e.g., factory corners, underground parking lots). MEC, on the other hand, supports high-density device access through distributed deployment. Together, these technologies provide combined coverage and capacity improvements: IRS extends coverage, while MEC helps distribute the load across the core network.

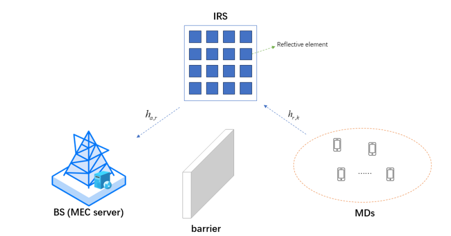
This paper focuses on the integration of IRS and MEC, exploring how to effectively leverage IRS as an emerging wireless communication technology. The following sections will provide an in-depth examination of various IRS-MEC scenarios and optimization models for IRS phase shift coefficients.

III. Scenarios for IRS and MEC Integration

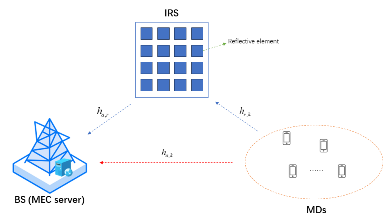
In this section, we summarize specific scenarios of an IRS-assisted MEC network, covering various MEC contexts. While our list may not encompass all possible scenarios, we intend to present a wide range of specific situations involving the integration of IRS and MEC, aiming to stimulate ideas for future research. The categorization of these scenarios is based on factors such as the number of IRS, the number of base stations (BS), and the status of the IRS, as explained below.

A. Single Static IRS-Single BS (w/o MD-BS link)

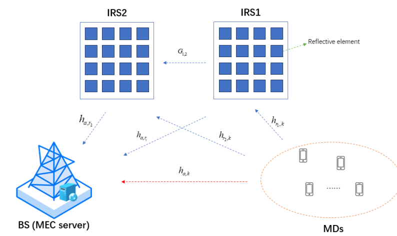
As shown in Fig. 1a, we present a straightforward scenario that effectively demonstrates the capabilities of the IRS [2], [6]. In this scenario, the MD finds itself in a "dead zone",



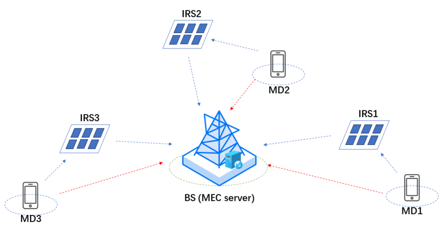
(a) Single Static IRS-Single BS (w/o MD-BS)



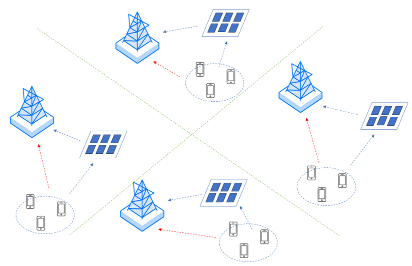
(b) Single Static IRS-Single BS



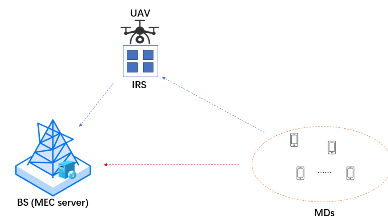
(c) Multi Static IRS-Single BS



(d) Multi Static IRS-Single BS (single MD)



(e) Multi Static IRS-Multi BS



(f) Single Dynamic IRS-Single BS

Fig. 1: Scenarios for IRS and MEC Integration

characterized by either the absence of a communication link between MDs and BS or a suboptimal direct communication link. In such situations, we can enhance the channel model by employing the data transmission-reflection mode of the IRS.

We introduce a general MEC deployment assisted by an IRS. This configuration involves a BS equipped with a single antenna, an IRS comprising N reflecting elements, and an MD equipped with a single antenna. The resulting channel model for the system, assisted by the IRS, can be outlined as follows:

$$h_k = h_{a,r}\Theta h_{r,k} + n, \tag{1}$$

where $h_{a,r} \in \mathbb{C}^{1\times N}$ represents the channel parameters between the BS and the IRS, $h_{r,k} \in \mathbb{C}^{N\times 1}$ denotes the channel parameters between the IRS and the k-th MD, where n is the additive white Gaussian noise at the device with zero mean and variance σ^2, and Θ denotes the phase shift matrix of the IRS, expressed as: $\Theta = diag\left(a_1 e^{j\theta_1}, \cdots, a_N e^{j\theta_N}\right)$, where $a = (a_1, a_2, \cdots, a_N)$ represents the amplitude reflection coefficient vector and $\theta = (\theta_1, \theta_2, \cdots, \theta_N)$ represents the phase shift coefficient vector. In order to reduce the energy consumption of the system as a whole, the amplitude reflection coefficient is generally set to 1, and the most important decision we need to make is often the phase shift reflection coefficient θ of the IRS.

B. Single Static IRS-Single BS

The primary difference in Fig. 1b compared to the scenario in Fig. 1a is that there is a direct communication link between MDs and BS. The IRS is better positioned to reflect the multi-path effects of signal propagation. Through the simultaneous utilization of the IRS reflection link and the direct communication link, we can amplify the signal strength at the receiving end, resulting in an improved quality of the received signal.

While the first scenario in Fig. 1a emphasizes the reflective performance of the IRS, this scenario highlights the enhanced overall performance of the IRS. The channel model for this scenario incorporates the direct link between MDs and BS, denoted as $h_{a,k}$, building upon the foundation of the channel model in Fig. 1a.

C. Multi Static IRS - Single BS

In a single IRS scenario, there exists an additional MD-IRS-BS communication link compared to a scenario without an IRS. In the context of multi-IRS assistance, multiple IRSs are introduced in addition to a single IRS, as depicted in Fig. 1c. In comparison with the scenario shown in Fig. 1b, IRS1 and IRS2 are now included, resulting in three additional communication links. Notably, the most distinctive link is the communication path connecting the MD to the BS through the reflection of IRS1 and IRS2. To model the communication dynamics in this scenario, we extend the communication model established for a single IRS. Consequently, we formulate the channel model for MD-IRS1-IRS2-BS as follows:

$$h_{a,r1}\Theta_1 G_{12}\Theta_2 h_{r2,k}, \tag{2}$$

where Θ_1 and $\Theta 2$ represent the phase shift coefficient matrices of IRS1 and IRS2, respectively (with the amplitude reflection coefficient vector consisting of elements all equal to 1), and $G12$ denotes the channel parameters easily IRS1 and IRS2. Using the two IRS-assisted channel models outlined above, we can readily compute the channel model between the MD and the BS, as well as extend this to scenarios involving three IRS, four IRS, and other auxiliary configurations.

D. Multi Static IRS-Single BS (Single MD)

As illustrated in Fig. 1d, this scenario represents a MEC setup with multiple IRS assistance [7]. The difference from

TABLE II: Different MEC-IRS frameworks

Framework	Direct link of BS-MD	No. of IRSs	Installation	No. of BSs
Fig. 1a	No	Single	Static	Single
Fig. 1b	Yes	Single	Static	Single
Fig. 1c	Yes	Single	Static	Single
Fig. 1d	Yes	Multi	Static	Single
Fig. 1e	Yes	Multi	Static	Multi
Fig. 1f	Yes	Single	Dynamic	Single

the previous scenario lies in the fact that each MD in this configuration transmits data to the BS with the aid of a dedicated supporting IRS. Following data transmission, the scenario involves optimizing the IRS dependency coefficient matrix to suit the diverse communication environments and offloading tasks of each MD. This scenario is extendable to a multi-cell design. Considering the proximity of each MD, it is assumed that the communication environments for MDs in close vicinity are relatively similar. This assumption allows IRS phase shifting to be optimized to improve the communication performance of multiple MDs.

E. Multi Static IRS-Multi BS

As depicted in Fig. 1e, the primary difference in this scenario compared to the previous MEC scenario in Fig. 1d lies in the variable number of BS, specifically within the multi-MEC server scenario. We can describe this scenario as a multi-cell design, where each cell incorporates an IRS to enhance MD-BS communication within that cell. While it remains an overall multi-IRS assisted scenario, the optimization methodology significantly differs from the aforementioned multi-IRS scenario. In this context, if the phase shift coefficient matrix slated for optimization is independent of the parameters in other cells, the optimization can be conducted using the previous single IRS optimization model. This approach proves advantageous by markedly reducing the complexity of the optimization process.

F. Single Dynamic IRS-Single BS

As shown in Fig. 1f, the difference between this scenario and the previously introduced IRS-assisted MEC system communication scenario is that the IRS in this scenario is not static, but placed on a dynamically moving Unmanned Aerial Vehicle (UAV), which can make full use of its high mobility and deployment flexibility, thereby shortening the distance between the BS and the MD, and effectively avoiding serious damage caused by long-distance signal transmission. Generally, by optimizing the flight trajectory of the UAV and the phase shift coefficient matrix of the IRS, we can expand the communication range of the BS and make the MD obtain better communication performance. Similarly, in the scenario, we can also introduce drones with multiple IRS to provide better services for more MD, which we will not repeat here.

The scenarios discussed above focus primarily on a macro-level perspective of integrating IRS into MEC networks. However, it is also important to consider the inherent characteristics of the IRS itself. For each reflective element on the IRS, we can calculate its energy consumption (although relatively low) and selectively deactivate certain elements when they are not required for the transmission task. Additionally, the varying amplitude reflection coefficient can be adjusted to further optimize performance and efficiency.

G. STAR-IRS

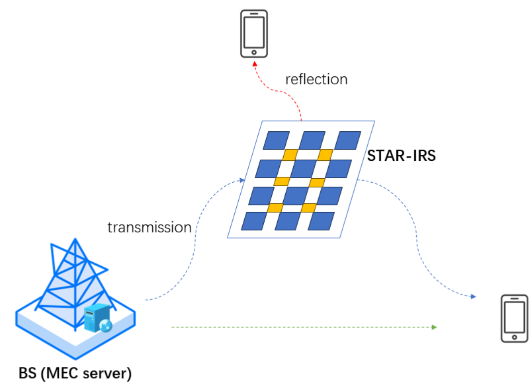


Fig. 2: Architecture combining the STAR-IRS with MEC

In Fig. 2, we introduce a scenario that combines MEC with a specialized IRS, known as simultaneously transmitting and reflecting RISs (STAR-RISs) [8]. Unlike traditional IRSs, which have a limited reflection range of 180°, the STAR-IRS is capable of a full 360° reflection range, enabling more versatile and efficient signal propagation. This capability enables the system to not only capture the communication signal emitted from the BS to the MD positioned in front of the IRS, but also to transmit the signal to an MD located behind the IRS via refraction. This innovative design effectively extends the IRS's communication range, thereby significantly enhancing the performance of the system.

H. Potential Applications and Specific Deployment Methods

Technologies that combine IRS and MEC can be applied in various domains:

- **Smart Cities**: The integration of IRS and MEC optimizes communication networks within cities, enhancing efficiency and enabling smarter urban living. For instance, in disaster emergency communications, drones equipped with mobile IRS can extend and reflect emergency signals to rescue areas, providing temporary network coverage.
- **Industrial IoT**: The integration of IRS and MEC enables real-time communication and data processing in the Industrial IoT, enhancing the efficiency of industrial production. Due to the reconfigurable nature of IRS, it can address wireless signal interference in equipment-dense environments, such as intelligent manufacturing workshops. By adjusting the phase shift factors, IRS strengthens the data signal while weakening noise, improving communication quality in these challenging environments.
- **Healthcare**: The integration of IRS and MEC facilitates applications such as telemedicine and remote monitoring in healthcare, improving the quality and efficiency of healthcare services. For example, the IRS can assist communication between Internet of Medical Things (IoMT)

devices within a hospital, ensuring reliable and efficient data transmission.

- **Intelligent Transportation**: In intelligent transportation systems, the integration of IRS and MEC enhances traffic flow and safety by providing intelligent and responsive traffic management solutions. For instance, IRS on highways can improve communication between vehicles and Roadside Units (RSUs). It can also reflect traffic signal data to vehicles in visually obstructed areas, such as those blocked by large vehicles, ensuring seamless communication and timely information delivery.

In this paper, we will not delve into the technical intricacies of combining IRS and MEC. Instead, our focus will be on exploring the various scenarios where IRS can be integrated with MEC, along with different models for optimizing the IRS phase shift coefficients. In the next section, we will present several approaches to effectively optimize these phase shift coefficients.

Specific IRS Deployment Methods: IRS is typically used for blind spot coverage (e.g., indoor dead zones, underground garages), capacity enhancement (e.g., hotspots), or energy-efficient communication (e.g., reducing base station power consumption). The primary application areas include offices, shopping malls, and airports, where it addresses issues like Wi-Fi or 5G signal blockages (indoor). For outdoor applications, IRS extends base station coverage at the edges of communities, street corners, and between high-rise buildings. IRS implementation methods can be broadly classified into fixed and mobile deployments: Fixed installations are usually embedded in walls, ceilings, or lampposts, while mobile deployments involve temporary setups on vehicles or drones, primarily for emergency communications.

IV. Optimization Models Combined with IRS

In IRS-based models, one of the key parameters that requires optimization is the phase shift coefficient (or phase shift coefficient matrix), which is often the most challenging aspect of IRS model optimization. In this section, we outline several methods or models that can be employed to optimize the IRS phase shift coefficient matrix. It is important to note that no single model outperforms the others, and we cannot cover all possible optimization approaches. However, the methods presented here aim to provide valuable insights for future research in this area. The optimization models discussed focus on how to optimize the phase shift coefficient matrix of the IRS (with the amplitude coefficient generally set to 1) in the IRS-assisted MEC scenario to obtain improved system performance.

Understanding the structure of the IRS phase shift coefficient matrix is critical. In general, the phase shift coefficient vector of the IRS can be categorized into discrete and continuous types. The discrete type involves N energy levels for each reflecting element, typically represented by a set of discrete phase shift values $\{0, \Delta\theta, \cdots, (N-1)\,\Delta\theta\}$, where $\Delta\theta = 2\pi/N$. On the other hand, the continuous type requires a continuous phase shift value, denoted as $\theta \in [0, 2\pi)$.

When considering the difficulty of optimization, discrete phase shift coefficient matrices are often more feasible for finding optimal values, as they can be implemented in practical scenarios. In contrast, obtaining optimal values for continuous phase shift coefficient matrices is not realistic. A conventional approach is to first treat the problem as a continuous case during model construction, and then select the closest discrete value from a set of discrete values as the optimal phase-shift coefficient matrix for the current discrete IRS. Although this may result in some performance loss, it is a practical compromise.

In the following, we summarize several methods for solving the optimal IRS phase shift coefficient matrix in MEC scenarios. However, specific scenarios may require optimization tailored to their unique characteristics.

A. Convex Optimization Model

For the optimization of the dependency coefficient matrix of the IRS, various convex optimization methods can be applied, including the semi-positive definite relaxation method (SDR) and other techniques.

Although the work in [9] does not incorporate the MEC model, their proposed optimization goal is to minimize the transmission energy consumption of beamforming. They utilize the SDR and the alternate optimization idea to optimize the continuous IRS phase shift coefficient matrix algorithm model, which can be referenced in similar contexts. In general, the approach involves representing $w_i = e^{j\theta_i}$ and converting the objective function into traces about the matrix W. Subsequently, the convex programming SDR model is employed to solve the problem. Handling the constraint that the matrix W rank is equal to 1 is a crucial aspect, often addressed through methods such as Gaussian random. Similarly, Liu *et al.* [10] used IRS to enhance the communication performance of the Device-to-Device (D2D) system. The optimization of the phase shift coefficient of the IRS involves a quadratic approximation of the objective function, followed by iterative optimization of the phase shift coefficient. This approach falls under the category of convex optimization.

B. Heuristic Algorithmic Models

For the optimization of discrete phase shift coefficient matrices, we can also consider using heuristic swarm intelligence algorithms, such as evolutionary algorithms, ppaper swarm algorithms, etc.

Huang *et al.* [6] investigated MEC networks assisted by a single IRS. The primary optimization objective is to minimize the long-term average energy consumption of all MDs while adhering to the constraints of long-term data queue stability. After solving the optimal offloading power by convex optimization methods (Lagrangian dual method, etc.), an optimization model based on population genetic algorithm is designed to find the optimal discrete phase shift coefficient matrix of the IRS. Some other works focus mainly on maximizing the total data throughput of the system, with the target to optimize the discrete phase shift coefficient matrix of the IRS, and to design an iterative optimization algorithm based on a population genetic algorithm. Souto *et al.* [11] employ a swarm optimization algorithm from swarm intelligence to optimize the energy consumption associated with the smallest beamforming. In this case, a discrete IRS dependency coefficient matrix is utilized. While the framework does not specifically involve MEC, the concept of leveraging heuristic algorithm optimization can provide valuable insights and references for related scenarios.

C. Deep Learning-based Models

The utilization of Deep Neural Network (DNN) models to solve IRS optimization problems provides a clear distinction between optimizing the discrete and continuous IRS dependency coefficient matrices. In the context of Deep Reinforcement Learning (DRL), the distinction between discrete and continuous action spaces is analogous to the optimization of the IRS phase shift coefficient. In scenarios where the optimization objective is to maximize long-term average data throughput [12], the phase shift coefficient matrix of the discrete IRS is optimized. For this purpose, the Double Deep Q-Network (DDQN) model is employed [7]. On the other hand, when optimizing the continuous IRS phase shift coefficient matrix, algorithms such as Deep Deterministic Policy Gradient (DDPG) within DRL frameworks can be applied to find the optimal phase shift values.

D. Peculiarities (Trigonometric Inequalities)

In the general case, with the channel model $h_k = h_{a,r}\Theta h_{r,k} + h_{a,k} + n$ assisted by IRS, we can express the SNR of the received signal as $|h_{a,r}\Theta h_{r,k} + h_{a,k}|^2 P_k/\sigma^2$, where P_k indicates the transmission power of k-th MD, and σ^2 represents the noise power. In scenarios where the data transmission power and the channel parameters of MD-BS, MD-IRS, and IRS-BS are known, and a high SNR is desired, the optimal continuous IRS dependency coefficient matrix can be obtained by using the trigonometric inequality: $\theta^* = \mathrm{mod}\left(2\pi, phase\left(h_{a,k}\right) - phase\left(h_{a,r}h_{r,k}\right)\right)$, where the $phase$ function refers to the angle value of the $e^{j\theta}$.

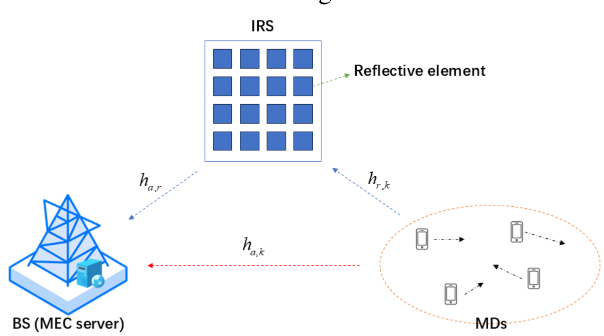


Fig. 3: Diagram of the system model

The work in [13] aligns with the described scenario. Although a DRL model is utilized to determine optimal values for other parameters, the trigonometric inequality method is employed to solve the solution to find the optimal IRS dependency coefficient matrix. The work in [14] primarily focuses on enhancing communication system performance. While the main emphasis is on optimizing the (active) transmit beamforming at the BS and the (passive) reflected beamforming of the phase shifter at the IRS to maximize the total received signal power at the user, it also corresponds to the objective of expanding the SNR. The optimization of the phase shift coefficient matrix of the IRS in this work also directly adopts the method of introducing trigonometric inequalities.

V. Simulation Experiments and Challenges

As shown in Fig. 3, we set up a classic IRS-assisted MEC task offloading scenario. Specifically, when a direct link exists between the MDs and the BS, we introduce the MD-IRS-BS link. We divide the operation time of the entire system into multiple time slots, during which the communication channel states between MD-IRS, IRS-BS, and MD-BS remain constant, or the channel coherence time exceeds the duration of a single time slot. Our focus is on determining the optimal task offloading decisions and resource allocation strategies by minimizing both long-term average energy consumption and ensuring long-term data queue stability. It is important to highlight that optimizing the IRS phase shift coefficient presents a significant challenge due to the inherent complexity of the optimization problem. To overcome this, we adopt a convex optimization approach to derive the optimal IRS phase shift coefficient. The schemes under comparison are as follows:

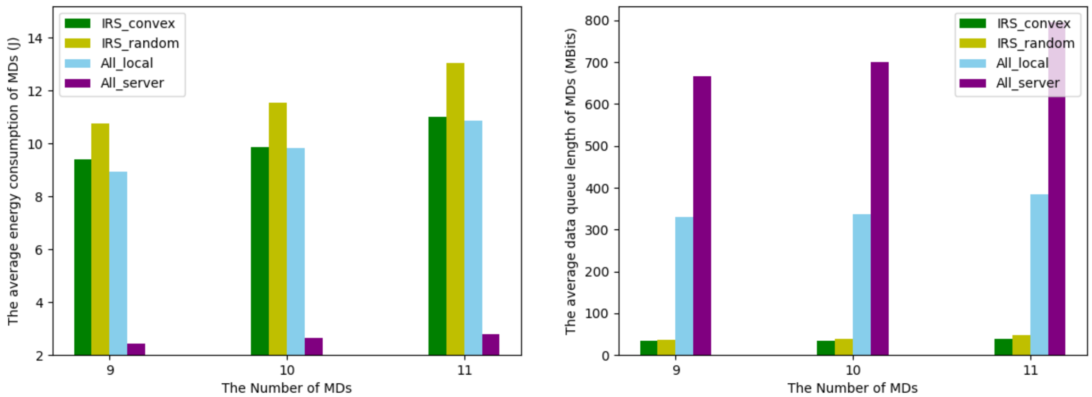
- IRS-random: This scheme utilizes random IRS phase shift coefficients [11];
- All-local: All user data is processed locally;
- All-server: All user data is processed on the MEC server.

As shown in Fig. 4, compared with the IRS-random model, the IRS-convex model is slightly lower than the IRS-random model in terms of data queue length, and the system energy consumption can be lower in terms of energy consumption. However, comparing the IRS-convex model with the All-local model and the All-server model, although the latter two can achieve lower energy consumption, the length of the data queue will be too long.

Although IRS has shown strong performance in enhancing communication, several challenges remain in its practical deployment, including: i) Frequent Adjustment of Phase Shift Coefficients: Due to the dynamic nature of the IRS reconfiguration in the communication environment, there is a need to frequently adjust the IRS phase shift coefficients, which significantly increases operational complexity. ii) Scaling to Large Reflector Sets: Most existing studies focus on scenarios with relatively small IRS reflector sets. However, in real-world deployments, when the number of reflector elements increases (e.g., 100 or 1000 elements), optimizing the phase shift factors becomes much more challenging. iii) Communication Model Limitations: Many studies rely on idealized communication models for IRS, which do not accurately reflect the real-world amplitude and phase shift characteristics. The discrepancy between the theoretical models and the actual performance of IRS systems remains a crucial issue that requires attention.

VI. Conclusion

The integration of IRS and MEC is one of the important research vectors that can make a tangible positive impact on future wireless communication systems. By leveraging the



(a) Energy consumption

(b) The length of data queue

Fig. 4: Aaverage energy consumption and average data queue length under different approaches

strengths of both technologies, the performance of communication systems can be significantly enhanced, and new use cases can be supported. This convergence can bring important changes in several vertical sectors like smart cities, industrial IoT, medical and health care, and finally promote an effective development of the digital age. This paper primarily addresses two key aspects, considering the diverse scenarios and complex optimization challenges in IRS-assisted MEC networks: the description of various IRS-assisted MEC scenarios and the exploration of different optimization methods for the IRS phase shift coefficients. With its low cost, low energy consumption, and minimal complexity, IRS has emerged as a crucial technology for enhancing communication. Meanwhile, MEC provides MDs with low-latency, energy-efficient computing resources. The synergistic integration of the advantages of both IRS and MEC holds significant promise for dramatically improving the performance of communication systems.

Acknowledgment

This work is supported by National Natural Science Foundation of China (62071327) and Emerging Frontiers Cultivation Program of Tianjin University Interdisciplinary Center.

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Biographies

Junhui Du received the BSc degree in mathematics from the Nanjing University of Information Science Technology, China, in 2021. He is currently working toward his Ph.D. degree in mathematics at the Center for Applied Mathematics, Tianjin University, Tianjin, China. His research interests include Internet of Things, deep learning, and mobile edge computing.

Huaming Wu received the B.E. and M.S. degrees from Harbin Institute of Technology, China in 2009 and 2011, respectively. He received the Ph.D. degree with the highest honor at Freie Universität Berlin, Germany in 2015. He is currently a professor at the Center for Applied Mathematics, Tianjin University. His research interests include wireless networks, mobile edge computing, Internet of Things and complex networks.

Anwer Al-Dulaimi received his Ph.D. in electronic and computer engineering from Brunel University in 2012 after receiving B.Sc. and M.Sc. honors degrees in communication engineering. He is currently a Senior Strategy Manager of Connectivity at Veltris, Toronto, Canada and Associate Professor at Zayed University in UAE. His research interests include 6G networks, cloud computing, V2X, and cybersecurity

Shahid Mumtaz received his M.Sc. degree from Blekinge Institute of Technology, Sweden, and his Ph.D. from the University of Aveiro, Portugal. He is currently a Professor at Silesian University of Technology and Nottingham Trent University. His research interests include MIMO techniques, Multi-hop relaying communication, cooperative techniques, cognitive radios, and so on.