Reconfigurable Intelligent Surface for Low-latency Edge Computing in 6G

Yueyue Dai, *Member, IEEE*, Yong Liang Guan, *Senior Member, IEEE*, Kin K. Leung, *Fellow, IEEE*, and Yan Zhang, *Fellow, IEEE*

***Abstract*—Edge computing, as one of the key technologies in 6G networks, establishes a distributed computing environment by deploying computation and storage resources in proximity to end-users. However, the dense deployment of base stations, cellular dead zones, and high dynamic of mobile devices may cause serious interference issues and weak signal propagation, which will severely affect the transmission efficiency of edge computing and cannot support low-latency applications and services. Reconfigurable intelligent surface (RIS) is a new technology that can enhance the spectral efficiency and suppress interference of wireless communication by adaptively configuring massive low-cost passive reflecting elements. In this paper, we introduce RIS into edge computing to support low-latency applications, where edge computing can alleviate the heavy computation pressure of mobile devices with ubiquitously distributed computing resources, and RIS can enhance the quality of wireless communication link by intelligently altering the radio propagation environment. To elaborate the effectiveness of RIS for edge computing, we then propose a deep reinforcement learning (DRL)-based computation offloading scheme to minimize the total offloading latency of mobile devices. Numerical results indicate that the RIS-aided scheme can improve wireless communication data rate and reduce task execution latency.**

***Index Terms*—Reconfigurable intelligent surfaces, low-latency edge computing, 6G, deep reinforcement learning**

I. Introduction

The proliferation of Internet of Things (IoT) devices and Artificial Intelligence (AI) applications brings totally different features, such as data-driven, intelligence support, and computation-intensive, and poses more stringent requirements (i.e., lower latency, denser connectivity, higher data rates) that current 5G cannot satisfy. The future six-generation (6G) wireless communication network is expected to evolve itself by integrating emerging technologies in wireless communication and networking to support various new and unknown services. Edge computing, as one of the critical emerging technologies, is proposed to provide distributed computation, storage, and powerful data-processing capability close to users. In edge computing, devices can offload their computation-intensive tasks to nearby distributed base stations (BSs) to process.

Low-latency for 6G is of capital importance as it is essential to ensure punctual and accurate end-to-end latency for future use cases. By deploying computation resource on the edge servers, edge computing can shorten the distance to access computation resource for mobile devices, thus reducing task transmission delay. There has been a considerable amount of work focusing on low-latency edge computing. The authors in [1] proposed to offload computation tasks to lightweight and distributed vehicular edge servers to minimize task processing latency in vehicular edge computing networks. The authors in [2] integrated digital twin and federated learning in edge computing, in which devices can migrate real-time data processing and computation to the edge plane to process. The authors in [3] considered the latency and reliability requirements of mission-critical applications and proposed a two-timescale task offloading scheme where user–server association is decided in the long timescale and dynamic task offloading is executed in the short timescale. The authors in [4] formulated the delay that offloaded task experiences and then designed a dynamic task offloading and scheduling strategy with the heterogeneous latency constraints of IoT applications to make the offloading decision. Although edge computing can reduce latency by shortening transmission distance and providing in proximity to user processing capability, the dense deployment of BSs may cause serious network interference and weak signal propagation, thus resulting in very low wireless transmission rate and very high task transmission delay. With the popularity of edge computing, there will inevitably be more task transmission requirements, but current low wireless transmission rate will severely limit the efficiency of edge computing.

Recently, reconfigurable intelligent surface (RIS) has been envisioned as a revolutionary technique in wireless communication to enhance spectral efficiency and suppress interference [5]. RIS consists of massive passive reflecting elements, which can be considered as antenna elements to modify the signal propagation environment. Specifically, by intelligently adjusting both amplitude and phase shift of passive reflecting elements, it can enhance the received signal power, thus improving wireless transmission rate [6]. Compared to traditional active relay techniques, RIS can control the reflective coefficients in real-time to achieve signal reflection without interference and passively reflect the incident signals without power amplification. Moreover, the low hardware cost of RIS elements allows for their easy and dense deployment in wireless networks with high array/passive beamforming gain. All the above appealing advantages have motivated plenty of researchers to integrate RIS into conventional wireless networks to enhance communication performance. For example, the authors in [7] considered an RIS-based downlink multi-

Y. Dai and Y. Guan are with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore (email:yueyuedai@ieee.org; eylguan@ntu.edu.sg).

K. K. Leung is with the Department of Electrical Electronic Engineering, Imperial College London, London SW7 2BT, U.K. (e-mail: kin.leung@imperial.ac.uk).

Y. Zhang is with the Department of Informatics, University of Oslo, Norway; and also with Simula Metropolitan Center for Digital Engineering, Norway (email: yanzhang@ieee.org).

user communication from a multi-antenna BS and developed an optimization algorithm to optimize RIS phase shifts and downlink transmission powers for maximizing system energy efficiency. The authors in [8] proposed RIS-assisted unmanned aerial vehicle (UAV) systems to improve the coverage and reliability of UAV communication by installing RIS on a building to reflect the signals transmitted from a ground UAV.

In this paper, we propose an RIS-empowered framework for edge computing to support low-latency applications, in which edge computing can alleviate the heavy computation pressure of mobile devices and reduce task processing latency with ubiquitously distributed edge servers. RIS can enhance the quality of wireless communication links in the computation offloading process by intelligently altering the radio propagation environment. The main contributions of this paper can be summarized as follows:

- We propose an RIS-empowered edge computing framework. By leveraging RIS to enhance the signal propagation environment, this framework can reduce task transmission time, while also improving the accessibility of edge computing service.
- We present the typical edge computing scenarios, i.e., mobile edge computing (MEC), vehicular edge computing (VEC), and digital twin edge networks (DITEN), and elaborate the benefits of RIS for these networks.
- We exploit an advanced DRL algorithm to design an RIS-assisted computation offloading scheme to minimize the total task execution latency of mobile devices by jointly optimizing RIS coefficients, computation resource, and offloading policy. Numerical results demonstrate the effectiveness of the RIS-assisted offloading scheme.

The rest of this article is organized as follows. The next section proposes an RIS-empowered framework for edge computing, along with the main characteristics and key challenges. Then, an RIS-assisted computation offloading scheme to minimize the total task execution latency is designed. In section IV, numerical results demonstrate the proposed DRL scheme. The final section concludes the article.

II. RIS EMPOWERED LOW-LATENCY EDGE COMPUTING

The emerging applications, such as location-based virtual/augmented reality, real-time online gaming, and ultra-high-definition video streaming, are computation-intensive and latency-critical. To support the high quality-of-service (QoS) requirement of these applications, edge computing moves the computation/storage capabilities from cloud servers to the edge of wireless networks for avoiding the long transmission delay between mobile devices and cloud servers. However, edge computing only shortens the distance to access the computation resource, but does not involve the performance improvement on wireless communication links. The recent proposed RIS can change the wireless propagation environment to enhance the spectral efficiency with potentially significant benefits such as high energy-efficient, high-speed, massive-connectivity, and low-latency. In this paper, we propose an RIS-aided edge computing for 6G to support low-latency services and applications, as shown in Fig. 1.

The proposed framework consists of two layers: the RIS-aided communication layer and the AI-supported edge intelligence layer. In the RIS-aided communication layer, RIS elements are distributively installed on the surface of building facades, to improve the propagation conditions and increase the quality of wireless communications. The edge intelligence layer is constructed of diverse distributed edge servers. With the combination of edge resources and AI algorithms, these edge servers are cooperated to enable intelligent police designing, QoS requirement perception, resource management, and network topology monitoring. In the following, based on the specific characteristics of terminals and enabling technologies, we consider three typical edge computing scenarios, i.e., MEC, VEC, and DITEN, and describe how RIS improving the performance of these networks.

A. RIS for Mobile Edge Computing

In an MEC network, there are three types of distributed network entities. The first type is mobile devices, such as smartphones. Each mobile device is equipped with plenty of intelligent applications, which have strict requirements on computation and caching resources (i.e., CPU, GPU, and memory). Although current powerful devices have a certain amount of local computation and caching resources, it is still insufficient to run some machine learning-based applications with a required low latency. The second type of network entity in the MEC network is BSs and access points (APs). Different from traditional radio access points, these BSs and APs are equipped with computing and storage resources, so that they not only can provide radio interfaces to mobile devices for enjoying instant wireless communication but also can cooperate to offer sufficient computational capacity and powerful data-processing ability. In MEC networks, devices can enjoy ubiquitous edge computing and caching services.

Although MEC can efficiently avoid the long transmission latency from BSs to remote cloud servers, it is still quite challenging to provide ultra-low latency services. On one hand, with the dense deployment of edge servers, there will be more and more data transmission requirements in the process of computation offloading, edge caching, and content delivery, which may aggravate network interference and increase transmission delay. On the other hand, MEC cannot improve the quality of wireless communication links because it does not consider the adjustment of the wireless channel and radio propagation environment. In current wireless communication, there are three typical methods to increase wireless communication data rate. The first one is to deploy more heterogeneous nodes such as small base stations (SBSs) to increase access availability and spectrum utilization. The second one is to add more antennas at the BSs to enhance channel gain with massive multiple-input-multiple-output (MIMO). The third one is utilizing a higher frequency band such as millimeter wave to expand the available bandwidth. These techniques are promising but they incur high hardware and energy cost, and complicated signal processing issues.

In MEC networks, we utilize RIS to enhance the performance of wireless communication. A typical RIS is a planar

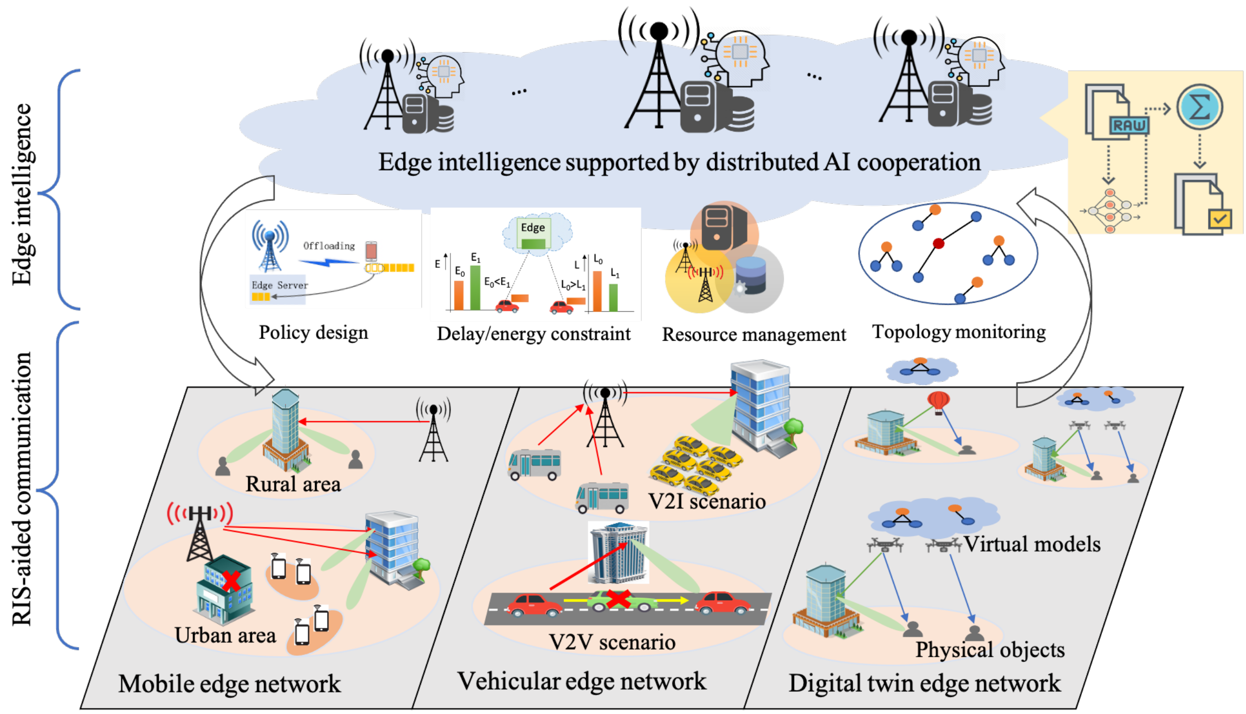

Fig. 1: The framework of RIS-aided edge computing

surface with a large number of passive, low-cost, and low-energy consuming reflecting elements. It is usually deployed on the facade of a high-rise building to assist wireless communication. However, there is a big difference between RIS and BS. That is, BS has computing and AI-processing capabilities, but RIS is a just signal propagation device. Due to this difference, we consider RIS as the third type of network entity in the proposed networks. Although RIS can passively reflect the impinging signals, it possesses an appealing advantage for mobile edge computing. As shown in the first block of Fig. 1, the deployment of RISs in both urban and rural environments can enhance the effectiveness of wireless communication and edge services:

- In an urban environment, a large number of buildings and the big size of each building may become a very troublesome obstacle to block the signals between mobile devices and BSs. Even if a device is located in the coverage of a BS, the device and the BS cannot directly communicate with each other. By deploying RIS in such an urban environment, RIS can build a device-RIS-BS link to enhance the accessibility of wireless communication.
- In a rural environment, many devices may be located outside the coverage of a BS. End users in such an area cannot enjoy the attractive computing, caching, and AI-based services which are provided by edge servers. Due to low hardware and energy cost, RIS is cost-effective and can be densely deployed in this area to expand the coverage of wireless transmission and edge services.

B. RIS for Vehicular Edge Computing

To reduce traffic accidents and improve traffic efficiency, VEC is proposed to support intelligent transportation applications such as road safety monitoring, automatic driving, and collision avoidance [9]. Vehicles in a VEC network have the following features: (1) sensing: vehicles can sense surrounding traffic with on-board devices, such as cameras, radars, and GPS; (2) communication: vehicles can exchange traffic information with each other via V2X communication, which includes vehicle-to-vehicle (V2V), vehicle-to-pedestrian (V2P), and vehicle-to-infrastructure (V2I) communications; (3) computing and caching: vehicles can execute parts of the data-processing tasks and store its own sensed information locally. Road-side units (RSUs) in a VEC network are located along a road to act as edge servers. RSUs are responsible for receiving the information sent from vehicles and processing the collected traffic information. Different from BSs, RSUs are equipped with some vehicular applications, such as path navigation, collision reminder, and traffic control.

Compared with the traditional MEC, the feature of high mobility makes VEC face the following challenges. Firstly, the high mobility of vehicles leads to highly frequent and dynamic topology changes. Thus, wireless links are easily disconnected, which will seriously deteriorate communication quality. Secondly, vehicles may switch among different edge servers, resulting in frequent handover. Frequent handover may cause service interruption and increase delay, thereby degrading user experience. Thirdly, massive sensing information, such as the current position of a vehicle and road condition in a specific area, is only valid in a specific duration or area. Therefore, a vehicle should complete task offloading or data transmission before leaving the specific area or data expiration.

To realize this, robust connection and high quality of V2X communication are required.

By densely deploying RISs in VEC networks and smart tuning the phase shift and amplitude of these reflecting elements, wireless environment, and network connectivity can be intelligently controlled and programmed. As shown in the second block of Fig. 1, the deployment of RISs can enable robust vehicular communication and flexible edge services:

- In a V2V scenario, RIS assists two vehicles to communicate with robust connections and high QoS of wireless links. Firstly, in an RIS-aided V2V scenario, a vehicle can communicate with another vehicle via the traditional V2V link and the added vehicle-RIS-vehicle link. Since the received signal is enhanced, the QoS of the V2V link is improved. Secondly, due to the highly dynamic of the vehicular network topology, the direct V2V link is easily blocked by other vehicles, as shown in the front case of the second block. In such a case, vehicle-RIS-vehicle can be acted as the main signal transmission link to maintain a robust connection. Moreover, different from current V2V communication that vehicles can only communicate with the nearest vehicle, RIS can expand the effective communication distance between vehicles and extend the maximum duration for allowing vehicles to accomplish task offloading and data transmission.
- In a V2I scenario, with the assistance of RIS, RSUs with edge computing and caching resources can support flexible computation offloading, full-duplex based data transmission, and large-scale emergency information broadcasting. In an RIS-aided V2I scenario, except for the single-hop communication between vehicles and RSUs, multi-hop RIS-assisted communications, such as vehicle-RIS-RSU, vehicle-RSU-RIS, and vehicle-RIS-RIS-RSU, are coexistence. Multi-hop communication enables flexible computation offloading and provides vehicles more offloading choices. That is, vehicles can choose the RSU with more computation resource instead of the nearest RSU to perform computation offloading. Further, RIS can operate in the full-duplex mode without any antenna noise amplification and self-interference. Thus, vehicles can upload the collected data and download content simultaneously via uplink and downlink, respectively. The parallel transmission will greatly increase network utility and user experience. Since RIS can make the signal evenly cover all vehicles in a specific area, it can help information broadcasting. That is, once finding a risk, RIS can notify as many surrounding vehicles as possible via broadcasting to avoid traffic hazards.

C. RIS for Digital Twin Edge Networks

DITEN is a new paradigm that utilizes digital twin to monitor real-time states of physical objects through software definition and accurately virtual modeling [10]. The concept of the digital twin was firstly presented by Grieves with three components, i.e., physical objects, virtual models, and the interconnection of data and information between them. Physical objects are responsible for providing their real-time features, properties, behaviors, and rules to construct virtual models. Virtual models are defined to record real-time states of physical objects, monitor dynamic changes of a physical network, extract the key features of physical components, and carry out optimization and prediction to improve the performance of the physical system.

The proposed DITEN consists of physical network entities layer and digital twin-empowered virtual layer. The physical layer is similar to the above two edge networks. But, there is a prominent difference between the above two networks and DITEN, that is DITEN has the virtual layer. In a DITEN, we consider each physical entity has a digital transformed model, namely DT model. There are two types of DT models. The first DT model is about the mobile device. This type of model mainly records the type of the collected data, the buffer size of the local dataset, the current location of a mobile device, and latency or computation resource requirement of on-device applications. The second type of DT model is about radio access points (i.e., BSs and UAVs) with the ability of edge intelligence. This type of model can predict real-time available communication, computing, and caching resources, monitor current wireless links to construct network topology, and execute policy decision-making. These DT models are not only highly consistent with the physical objects in terms of geometry and structure, but also able to simulate their spatio-temporal status, behaviors, functions, which is like a mirror of the physical objects. In addition, multiple DT models can intercommunicate with each other to realize global information sharing. Through global information sharing, we can have a relatively complete state of the physical network and can well predict, estimate, and analyze the network.

In a DITEN, since virtual models need a lot of data to perceive the real-time state of the network, the volume of data far exceeds a general edge network, and the speed to generate data is also faster than the general edge network. Therefore, the transmission pressure of the wireless link in DITEN is naturally greater. Moreover, to realize accurate DT modeling, the data of devices and BSs need to be transmitted without loss because any loss of important data may result in model distortion and failure mirror. Therefore, compared with MEC and VEC, DITEN has a more strict requirement on wireless transmission. To this end, we add RIS in DITEN to form a reliable communication link, as shown in the third block of Fig. 1. That is, the UAV transmission channels to the user compose the UAV-user link, the UAV-RIS links, and the RIS-user links. Since the UAV-RIS links and the RIS-user links build another wireless channel between UAVs and users to enhance the signal-to-noise ratio and decrease outage probability, it can provide reliable data transmission for distributed users. Since RIS is a kind of physical entity, we still need to construct a DT model for it. The phase shift and amplitude of reflecting elements are the key features of an RIS. Thus we consider the DT model of each RIS records real-time phase shift and amplitude of its reflecting elements.

D. Technical Challenges

RIS plays a critical role in constructing a flexible wireless communication environment and improving the quality

Objective	Channel	Brief descriptions
Minimize transmit power	AP-RIS-User + AP-user link	Jointly optimize transmit beamforming and RIS reflect beamforming [6]
Maximize energy efficiency	BS-RIS-User link	Jointly optimize RIS phase shifts and downlink transmit powers [7]
Improve coverage	Source-RIS-destination link	Performance impact of RIS on outage probability, bit-error rate, and capacity [8]
Improve coverage	RIS-assisted multi-hop	Jointly optimize beamforming vectors and RIS phase shift [11]
Increase wireless data rate	BS-RIS-User + BS-User link	Jointly optimize transmit power, beamforming vectors and RIS phase-shift matrix [12]
Increase wireless data rate	BS-RIS-User + BS-User link	Jointly optimize device selection, beamforming nd RIS phase shifts. [13]
Increase wireless data rate	AP-RIS-User + AP-User link	Jointly optimize RIS reflection coefficients, beamforming and energy partition [14]

TABLE I: Brief descriptions of RIS-assisted wireless communication.

of wireless communication links. Table I provides a brief summary of the most representative previous studies on RIS-assisted wireless communication, which refers to improve energy efficiency, expand communication coverage, and increase wireless communication data rate, respectively. However, deploying RIS in low-latency required edge systems imposes new challenges, which are discussed as follows:

- Intelligent RIS design: The optimal/sub-optimal reflecting coefficients are derived based on various optimization objectives, e.g., transmit power minimization, energy efficiency maximization, and rate maximization. However, due to the non-convexity of the objective function and constraints, it is challenging to use standard convex optimization techniques to design reconfigurable coefficients. Machine learning is an emerging tool which can intelligently learn and determine reconfigurable coefficients to achieve optimal operational decision.
- The combination of RIS and edge computing: The combination of RIS and edge computing aims to provide mobile devices with low-latency edge services. However, how to exploit and deploy RIS in edge computing to strike the best possible trade-off between latency and the QoS requirements of devices needs to be studied. Further, the inter-connection between RIS coefficients variables and edge computing variables also needs to be studied.
- Heterogeneous resource allocation: The process of RIS-aided edge computing may involve heterogeneous resource allocation and decision making, namely, communication, computation, RIS, and offloading. To improve resource utilization while satisfying low-latency requirement of devices, the joint optimization scheme should simultaneously determine offloading decision and allocate computation and communication resources for each device.

III. RIS-aided Computation Offloading

Recent advances in programmable meta-materials facilitate the construction of RISs to enhance spectral-efficiency with low energy and hardware cost. An RIS consists of an RIS controller and many passive reflecting elements, where each RIS reflecting element is able to dynamically program both the amplitude and the phase shift of the reflected signals for achieving signal enhancement and interference suppression. If RIS is deployed in an edge computing network, RIS can enhance wireless channel gain and increase the communication data rate between mobile devices and edge severs, thus reducing the offloading delay. In this section, we design an RIS-aided computation offloading scheme to minimize the total task execution latency of mobile devices.

As shown in Fig. 2, the network consists of a multi-antenna BS and K single-antenna mobile devices. The BS is equipped with an edge server for providing edge computing via wireless communications. The communications between mobile devices and the BS are assisted by a single RIS with N passive reflecting elements. Each mobile device has a computation-intensive task, which requires high computational capability as well as low execution latency to satisfy the requirement of QoS. The task can be denoted as $(D_k,\ C_k)$ where D_k is the data size of task k, C_k is the required computation resource for computing unit bit. We consider each task can be divided into two parts, one part is processed locally (i.e., $1-x_k$) while the other part is offloaded to the edge server to process (i.e., x_k). Thus, the task execution latency is determined by the local computation and computation offloading. Among them, local computation latency is mainly related to the computational capability of each mobile device (i.e., f_k^l). The latency of computation offloading involves task transmission time and edge computation time. Since the two parts are parallel executed (i.e., local computation conducts simultaneously with the process of computation offloading), the total task execution latency is equal to the maximal value of the two processes.

In the process of computation offloading, the offloaded task transmitted from mobile devices to edge servers via wireless channel may suffer high propagation loss due to random channel fading and interference issues. To establish effective and stable communication, in Fig. 2, RIS is deployed in the system to assist computation offloading for a higher wireless communication rate. With the presence of the RIS, the wireless channel does not only includes the direct device-BS link, but also includes the reflected device-RIS-BS link. Because of adding the reflected device-RIS-BS link, the received power gain and the channel capacity gain can be increased. Thus, RIS can improve the wireless transmission rate. Here, we denote the channel vector of the direct device-BS link as $\mathbf{h}_k^d$. The reflected channel of the device-RIS-BS link has three components, i.e., device-RIS link, RIS reflection with phase shifts, and RIS-BS link. We denote the channel vectors of the device-RIS link and RIS-BS link as $\mathbf{h}_k^r$ and $\mathbf{h}^H$ respectively. The reflection-coefficients of RIS can be denoted as $\Theta = \text{diag}(\beta_1 e^{j\theta_1}, \beta_2 e^{j\theta_2}, ..., \beta_N e^{j\theta_N})$, where β_n and θ_n are the amplitude and phase shift of n-th RIS element, respectively. Since the channel from the device to the BS includes both the direct link (device-BS link) and the reflected link (device-RIS-BS link), the effective channel gain can be expressed as $\mathbf{g}_k = \mathbf{h}_k^d + \mathbf{h}^H \Theta \mathbf{h}_k^r$, where $\mathbf{h}_k^d$ is the channel gain of the device-BS link and $\mathbf{h}^H \Theta \mathbf{h}_k^r$ is the

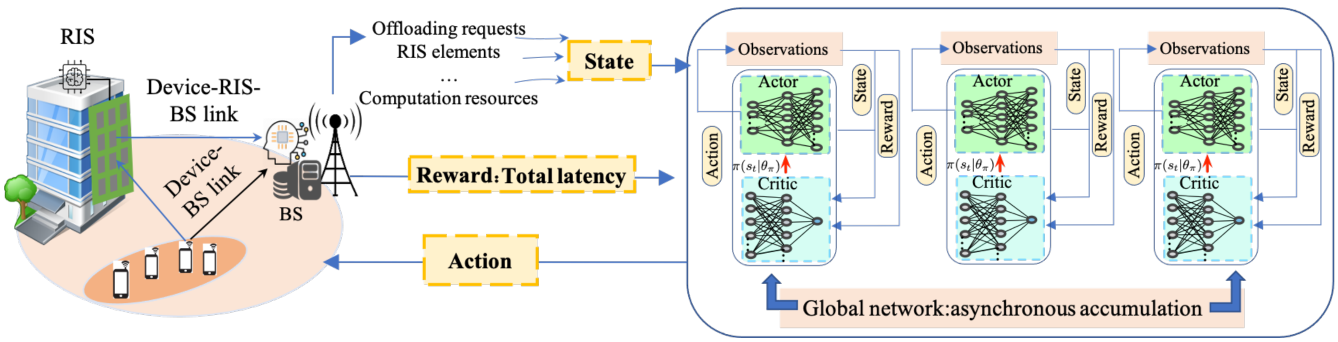

Fig. 2: RIS-aided Computation offloading with DRL

channel gain of the device-RIS-BS link. Thus, the maximum achievable wireless transmission data rate can be written as $R_k = B\log_2(1+\frac{p_k|\mathbf{w}_k^H\mathbf{g}_k|^2}{\sum_{j=1,j\neq i}^{K}p_j|\mathbf{w}_i^H\mathbf{g}_k|^2+\sigma^2})$ where B is the bandwidth of the system. By properly adjusting phase shift and amplitude of RIS elements, the wireless communication rate for computation offloading can be improved. To minimize the total task execution latency, it is imperative to jointly optimize both communication and computation. The minimization problem to jointly optimize RIS configuration, computation resource, and offloading partition can be formulated as

$$\min_{x,f,\beta,\theta} \sum_{k\in\mathcal{K}} \max\{D_kC_k\frac{1-x_k}{f_k^l}, D_kC_k\frac{x_k}{f_k^s}+D_k\frac{x_k}{R_k(\mathbf{g}_k)}\}$$

$$s.t. \sum_{k\in\mathcal{K}} f_k^s \leqslant F^s,\ 0\leqslant f_k^s \leqslant F^s, k\in\mathcal{K} \quad (1a)$$

$$x_k, \beta_n \in [0,1], k\in\mathcal{K}, n\in\mathcal{N} \quad (1b)$$

$$0\leqslant \theta_n \leqslant 2\pi, n\in\mathcal{N} \quad (1c)$$

where f_k^s and F^s are the computation resource that BS allocated to task k and the total computation resource that BS has. Constraint (1a) ensures that the total computation resource of the BS allocated to all tasks cannot exceed F^s. Constraint (1b) and Constraint (1c) specify the range of the offloading partitions, the range of the amplitude and phase shift of the RIS elements, respectively. The formulated problem is generally a non-convex programming problem. It is difficult to solve it in real-time with traditional optimization technique, due to high computational complexity. The emerging DRL technique has great potential to address the complex optimization problem by applying adaptive modelling and intelligent learning. Thus we use recent advanced Actor-Critic based DRL to solve the formulated latency minimization problem.

We first reformulate the above optimization problem as DRL form with system state, action, and reward:

1) State: The state in DRL is a space to reflect the environment. The state consists of five components $S = (D_k, C_k, f_k^l, F_s, \Theta)$. In the environment, the BS assembles these information as a state and sends it to the DRL agent.

2) Action: The objective of an agent is to map the space of states to the space of actions. In this system, the action consists of four parts: $A = (x_k, f_k^s, \beta_n, \theta_n)$, where x_k is the offloading variable, β_n and θ_n are RIS reflection coefficients.

3) Reward: Based on current state and action, DRL agent obtains a reward from the environment. Since reward function is related to the objective function, in this scenario, the total task execution latency can be regarded as the reward function (i.e.,$\mathcal{R}^{imm}(s(t),a(t)) = -\sum_{k\in\mathcal{K}}\max\{D_kC_k\frac{1-x_k}{f_k^l}, D_kC_k\frac{x_k}{f_k^s}+D_k\frac{x_k}{R_k(\mathbf{g}_k)}\}$).

According to the state, action, and reward, we exploit asynchronous actor-critic DRL to solve the formulated problem. The asynchronous actor-critic DRL is an asynchronous learning algorithm which utilizes multiple agents to interact with its own environment and each agent contains a replica of the environment [15]. Specifically, the asynchronous actor-critic DRL consists of a global agent and several learning agents. The global agent accumulates all parameters of the learning agents and shares the updated parameters. The learning agent is Actor-Critic based, where *Actor* is used to generate actions and *Critic* is used to evaluate and criticize the current policy by processing the reward obtained from the environment. The *Actor* network is a deep neural network and the parameter is updated using policy gradient method. That is, at each training step, the parameter of *Actor* network is updated based on $\theta_\pi \leftarrow \theta_\pi + \alpha_\pi\sum_t \nabla_{\theta_\pi}\log\pi(s(t)|\theta_\pi)A_\pi(s,a)]$ where α_π is the learning rate of the actor network and $A_\pi(s,a) = \mathcal{R}^{imm}(s(t),a(t)) + \delta v_{\theta_v}(s(t+1)) - v_{\theta_v}(s(t))$. The *Critic* network is also a deep neural network and it updates the parameter based on : $\theta_v \leftarrow \theta_v + \alpha_v\sum_t \nabla_{\theta_v}(\mathcal{R}^{imm}(s(t),a(t)) + \delta v_{\theta_v}(s(t+1)) - v_{\theta_v}(s(t)))^2$ where α_v is the learning rate of the critic network.

IV. Numerical Results

In this section, we provide the numerical results to validate the effectiveness of the RIS-assisted computation offloading. We consider the network comprises a BS, 4 devices, and an RIS with multiple passive reflected elements. The path loss exponents for the channels from device to BS, device to RIS, and RIS to BS are set as 3.2, 2.8, and 2.8, respectively. The bandwidth is 5 MHz. The data size and required computation resources of each task are 800 KB and 2 GHz, respectively. The CPU cycles of devices and edge servers are 0.5 GHz and 5 GHz, respectively. We use TensorFlow to evaluate the Actor-Critic DRL algorithm, which has three fully-connected hidden layers with 128 neurons and one output layer with 8 neurons. To demonstrate the benefit of RIS in edge computing networks, we consider two benchmarks. The first benchmark is to offload computation tasks without RIS assistance. i.e., only through the direct device-BS link. The second benchmark is to offload

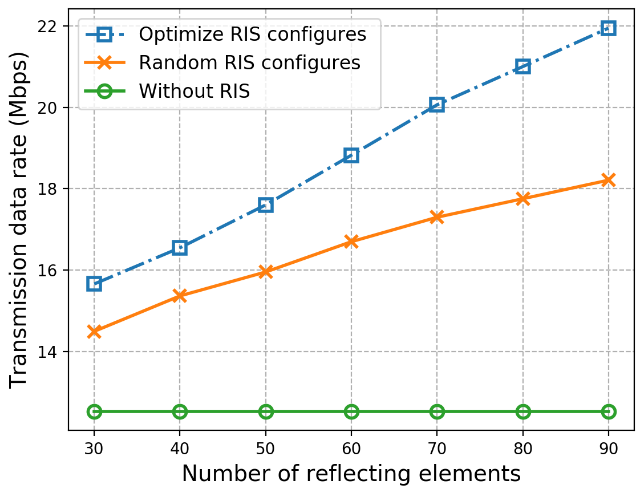

Fig. 3: Wireless transmission data rate v.s. number of reflecting elements with different schemes.

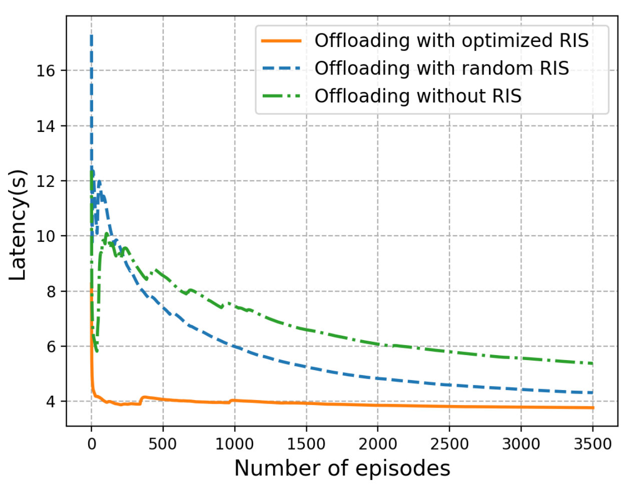

Fig. 4: Cumulative task execution latency under different schemes.

computation tasks via both device-BS link and device-RIS-BS link but the RIS configurations are set as random values.

Fig. 3 illustrates the comparison of wireless transmission data rate with respect to the number of reflecting elements under different RIS configuration schemes. From Fig. 3, it is first observed that the wireless transmission data rates of both RIS-aided schemes are higher than the wireless transmission data rate of the scheme without RIS-aided, which implies that RIS can assist in computation offloading. Secondly, the gap of wireless transmission data rate between without RIS-aided scheme and RIS-aided schemes increases with the number of reflecting elements. The reason is that increasing the number of reflecting elements can improve channel gain, which leads to a better data rate. Finally, due to the jointly optimize phase shift and amplitude, the wireless transmission data rate of the scheme with optimized RIS configures is higher than that of the scheme with random RIS configures.

Fig. 4 shows the total task execution latency of computation offloading under different RIS configuration schemes. Firstly, we can see the proposed DRL-based computation offloading algorithm converges in all cases and the cumulative task execution latency reduces with the number of episodes. Furthermore, the latency of RIS-aided offloading is lower than the latency without RIS-aided. The reason is that RIS-aided offloading with a higher transmission data rate can lead to a lower transmission latency. On the other hand, the lower transmission latency conversely results in more computation tasks being offloaded to the edge server, which leads to a further task execution latency reduction.

V. Conclusion

In this article, to support low-latency applications, we proposed RIS-aided edge computing to provide nearby computing service and high quality of wireless transmissions. In the proposed framework, RIS can enhance the coverage of wireless communication, support robust connection, and reduce data transmission pressure for edge computing. To clearly elaborate the effectiveness of RIS for edge computing, we proposed an RIS-assisted edge computing scheme to minimize the total offloading latency with actor-critic DRL algorithm. Numerical results indicated that RIS-aided scheme can efficiently improve wireless communication data rate and minimize task execution latency.

Acknowledgement

This research has partially received funding from XXX .

Yueyue Dai [M'20] (yueyue.dai@ntu.edu.sg) received the B.Sc. degree in communication and information engineering from the University of Electronic Science and Technology of China (UESTC) in 2014, and her Ph.D. degree from the same school in 2019. She is currently a research fellow at Nanyang Technological University, Singapore. From 2017 to 2019, she has been a visiting student with the Department of Informatics, University of Oslo, Norway. Her current research interests include wireless network, mobile edge computing, Internet of Vehicles, blockchain, and deep reinforcement learning. She was the recipient of the Best Paper Award from the IEEE International Conference on Communication Technology in 2019.

Yong Liang Guan (eylguan@ntu.edu.sg) obtained his Ph.D. from the Imperial College London, UK, and Bachelor of Engineering with first class honours from the National University of Singapore. He is a Professor of Communication Engineering at the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, where he leads the Continental-NTU Corporate Research Lab and the successful deployment of the campus-wide NTU-NXP V2X Test Bed. His research interests broadly include coding

and signal processing for communication systems and data storage systems. He is an Editor for the IEEE Transactions on Vehicular Technology.

Kin K. Leung (kin.leung@imperial.ac.uk) received his B.S. degree from the Chinese University of Hong Kong in 1980, and his M.S. and Ph.D. degrees in computer science from the University of California, Los Angeles, in 1982 and 1985, respectively. He worked his career at AT&T Bell Labs in 1986 and worked at its successor companies, AT&T Labs and Bell Labs Lucent Technologies, until 2004. Since then, he has been the Tanaka Chair Professor in Internet Technology at Imperial College London. He is the Head of Communications and Signal Processing Group in the EEE Department. His current research focuses on optimization and machine learning for design and control of large-scale communication, computer and sensor infrastructures. He was elected an IEEE Fellow (2001), received the Royal Society Wolfson Research Merits Award (2004-09), and became a member of Academia Europaea (2012) and an IET Fellow (2021).

Yan Zhang [F'20] (yanzhang@ieee.org) is a full professor at the University of Oslo. He is an Editor of several IEEE publications, including IEEE Communications Magazine, IEEE Network, IEEE Transactions on Green Communications and Networking, IEEE Communications Surveys & Tutorials, and IEEE Internet of Things. His current research interests include next generation wireless networks leading to 5G and cyber physical systems. He is Fellow of IEEE, Fellow of IET, elected member of Academia Europaea (MAE), elected member of the Royal Norwegian Society of Sciences and Letters (DKNVS), and elected member of Norwegian Academy of Technological Sciences (NTVA).

REFERENCES

[1] Y. Dai, D. Xu, S. Maharjan, and Y. Zhang, "Joint load balancing and offloading in vehicular edge computing and networks," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 4377–4387, 2019.

[2] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Low-latency federated learning and blockchain for edge association in digital twin empowered 6g networks," *IEEE Transactions on Industrial Informatics*, pp. 1–1, 2020.

[3] C.-F. Liu, M. Bennis, M. Debbah, and H. V. Poor, "Dynamic task offloading and resource allocation for ultra-reliable low-latency edge computing," *IEEE Transactions on Communications*, vol. 67, no. 6, pp. 4132–4150, 2019.

[4] H. A. Alameddine, S. Sharafeddine, S. Sebbah, S. Ayoubi, and C. Assi, "Dynamic task offloading and scheduling for low-latency iot services in multi-access edge computing," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 3, pp. 668–682, 2019.

[5] M. Di Renzo, A. Zappone, M. Debbah, M.-S. Alouini, C. Yuen, J. de Rosny, and S. Tretyakov, "Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and the road ahead," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 11, pp. 2450–2525, 2020.

[6] S. Abeywickrama, R. Zhang, Q. Wu, and C. Yuen, "Intelligent reflecting surface: Practical phase shift model and beamforming optimization," *IEEE Transactions on Communications*, vol. 68, no. 9, pp. 5849–5863, 2020.

[7] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, "Reconfigurable intelligent surfaces for energy efficiency in wireless communication," *IEEE Transactions on Wireless Communications*, vol. 18, no. 8, pp. 4157–4170, 2019.

[8] L. Yang, F. Meng, J. Zhang, M. O. Hasna, and M. D. Renzo, "On the performance of ris-assisted dual-hop uav communication systems," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 9, pp. 10 385–10 390, 2020.

[9] B. Yang, X. Cao, K. Xiong, C. Yuen, Y. L. Guan, S. Leng, L. Qian, and Z. Han, "Edge intelligence for autonomous driving in 6g wireless system: Design challenges and solutions," *arXiv preprint arXiv:2012.06992*, 2020.

[10] Y. Dai, K. Zhang, S. Maharjan, and Y. Zhang, "Deep reinforcement learning for stochastic computation offloading in digital twin networks," *IEEE Transactions on Industrial Informatics*, 2020.

[11] C. Huang, Z. Yang, G. C. Alexandropoulos, K. Xiong, L. Wei, C. Yuen, and Z. Zhang, "Hybrid beamforming for ris-empowered multi-hop terahertz communications: A drl-based method," *arXiv preprint arXiv:2009.09380*, 2020.

[12] S. Huang, S. Wang, R. Wang, M. Wen, and K. Huang, "Reconfigurable intelligent surface assisted mobile edge computing with heterogeneous learning tasks," *IEEE Transactions on Cognitive Communications and Networking*, 2021.

[13] H. Liu, X. Yuan, and Y.-J. A. Zhang, "Reconfigurable intelligent surface enabled federated learning: A unified communication-learning design approach," *arXiv preprint arXiv:2011.10282*, 2020.

[14] X. Hu, C. Masouros, and K.-K. Wong, "Reconfigurable intelligent surface aided mobile edge computing: From optimization-based to location-only learning-based solutions," *arXiv preprint arXiv:2102.07384*, 2021.

[15] V. Mnih, A. P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, and K. Kavukcuoglu, "Asynchronous methods for deep reinforcement learning," in *International conference on machine learning*. PMLR, 2016, pp. 1928–1937.