# Toward a Future Network Architecture for Intelligence Services: A Cyber Digital Twin-based Approach

Bin Tan, Yichen Qian, Hancheng Lu, Die Hu, Yuedong Xu, and Jun Wu

## Abstract

A cyber digital twin is a bridge connecting cyber and physical space, and it also provides a paradigm for intelligent service-oriented future network architectures. This article proposes a cyber digital twin-based future network architecture to support cross-space intelligent services and manage cross-space resources to meet the demand for diversified intelligent services. The cyber digital twin is introduced as a smart communication agent in the edge network to handle all physical object communication; thus, all the physical object data is acquired by its cyber digital twin. To meet the demand for diversified intelligent services, the proposed network architecture consists of a service analytical model, cross-space resource representation and management, and an autonomous configuration model. The service analytical model realizes the intelligent matching of new service requirements to resource requirements. Furthermore, the cross-space resource representation and management mechanism is based on reinforcement learning to ensure cross-space service consistency and resource utilization efficiency. Finally, the autonomous configuration model provides a unified intelligent configuration method for a large number of complex operations with cross-space devices. This article also proposes a cross-space resource management scheme that utilizes reinforcement learning to learn the optimal resource allocation strategy. The simulation results demonstrate its excellent performance.

## Introduction

As a large number of intelligent objects with perception, reasoning and execution abilities have gradually become elements of human production and life, the interactions and collaborations among intelligent objects and humans have become increasingly frequent. With the ever-increasing interactions between cyber and physical space, network functionality is being transformed from traditional information transmission to providing a new type of intelligent information services that integrate humans and machines. However, traditional cyberspace is separated from physical space, and it is inefficient to form closed-loop information services, including information transmission, intelligent decision-making, and online device control. By introducing cyber digital twins, we can reconstruct the complex information service chain of the physical space in cyberspace, which facilitates precise intervention and control of the physical space. In this way, we can achieve efficient cross-space service deployment, thereby reducing the interactions between cyber and physical spaces.

Existing digital twins have been widely used in applications such as smart manufacturing and smart cities. However, in these applications, digital twins are basically simulations of physical systems. In the automation industry, digital twins map physical products into the virtual world to visualize product structures, simulate product behaviors, and optimize product performances. Furthermore, the simulations are extended to all product life cycle stages. To the best of our knowledge, all existing digital twins are located in the application layer of the network protocol stack.

In contrast, the cyber digital twins we discuss here are extended to the network layer, and we use them to solve fundamental network issues. The current network suffers from some fundamental difficulties, including network address shortages and poor mobility and security. The root cause of these difficulties stems from the unified network identity and address. Current networks use Internet Protocol (IP) addresses to represent the network identity and network address simultaneously. The proposed future network separates the functionality of network identity and the network address and uses the cyber digital twin to identify the network object. The IP address only represents the network address. In network access, the cyber digital twin and IP address are associated and mapped. After network access, they are disconnected. In this way, traditionally difficult problems such as mobility and security are well solved. The cyber digital twin is always located in the edge network and cloud closest to the user and moves with the user.

Traditional Internet information services are implemented based on the service-oriented architecture (SOA) and do not rely on hardware and operating systems. They have good encapsulation, loose coupling and execution capabilities. The relevant research issues include service discovery, selection and combination. However, traditional atomic web services cannot fulfill complex business logic and functions due to their simple func-

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tions. With the development of a new generation of information technology, including cloud computing, the Internet of Things and big data, network services have become increasingly diverse. Later, infrastructure as a service (IaaS), software as a Service(SaaS), platform as a service(PaaS), and other forms of complex services emerged. With the explosive growth of service providers and consumers, traditional network architectures will not be able to meet the demands of variable and transient services. The organization and management of massive heterogeneous resources have become a performance bottleneck. New network architectures are urgently needed to address these problems.

The proposed framework of a cross-space service oriented network in this article is shown in Fig. 1. The physical object communicates with its cyber digital twin, which resides in the edge network; thus, the cyber digital twin plays the role of a smart communication agent to handle all the physical object communication. All the physical object data are naturally acquired by its cyber digital twin as a digital asset. These digital assets are important network resources for the upper service layer, which consists of a service analytical model, cross-space resource representation and management, and autonomous configuration of cross-space resources.

The traditional communication service establishes the connection between the terminal and the server, which is a process-oriented communication method. In this way, the physical communication object is anonymous, and the content of the communication is not saved. After the introduction of the digital twin, the communication service first establishes the connection between the physical entity and its cyber digital twin, and then the cyber digital twin on behalf of its physical entity requests services from the edge cloud and the core cloud. The communication process changes from end-to-end to end-to-cloud and from process-oriented to object-oriented. Furthermore, the user data retained by the cyber digital twin should become the digital assets of the physical object, and these digital assets can be used to construct and visualize the complex service chains in cyberspace.

The requirements for new information services deployed across spaces are complex. The introduction of physical space resources greatly expands the resource dimension, increasing the complexity of mapping the service requirement to the resource requirement. Through the analysis of the service attributes combined with knowledge-driven and data-driven methods, three-dimensional (3D) scene modeling and spatiotemporal evolution of physical space are visualized. The inference of complex information services in physical space and their resource requirements are realized.

To meet the cross-space intelligent service requirement, we need to establish a unified and complete network resource expression for cyber and physical space, which facilitates the mapping from services to converged resources with the help of a service analytical model. To support comprehensive cross-space deployment, cyber resources are abstracted as computing, storage, and bandwidth resources, and physical resources are expressed as cyber digital twins. With the unified resource expression, we introduce independent learning and evolution capabilities to support different information services in diversified service scenarios. Through the collaboration and competition of multiple agents, a distributed deep enhancement learning framework is designed to optimize cross-space resource management.

Based on unified cross-space resource representation and intelligent cross-space resource allocation, an autonomous configuration of resources across spaces is adopted to optimize the resource configuration strategy. Then, a special configuration instruction set is defined to execute the resource configuration operation. Intelligent configuration is used to reduce human intervention and ensure the accuracy and efficiency of cross-space resource configuration.

In this article, we make two contributions. First, we propose a cyber digital twin-based future network architecture for intelligent services.

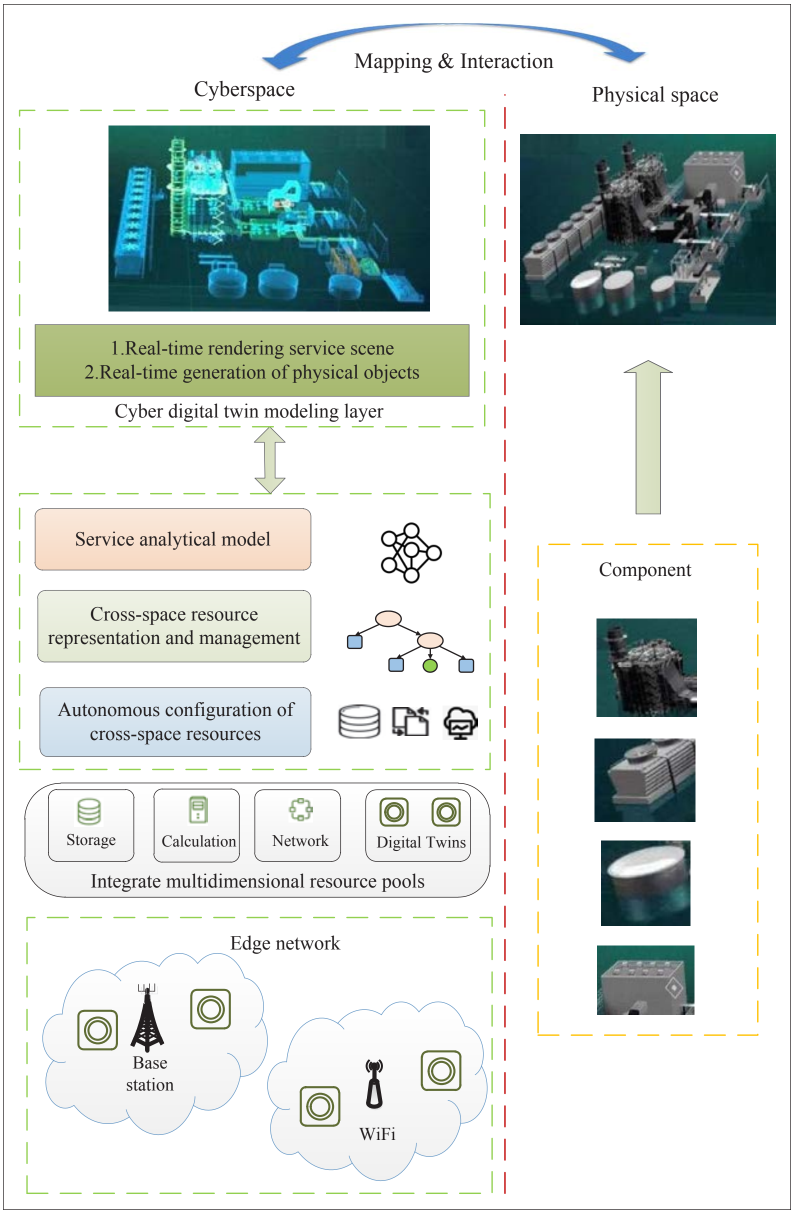


FIGURE 1. The proposed framework of the service oriented future network architecture.

The cyber digital twin modeling layer realizes the realistic modeling of physical objects in cyberspace, and the data required for the modeling are obtained through the digital assets obtained by the communication agent function.

Second, we propose an RL-based cross-space resource management scheme to learn the optimal resource allocation strategy. In the following sections, we present the system model for the proposed network architecture and a resource allocation scheme based on cyber digital twins. Then, the performance of the proposed scheme is evaluated. Finally, we conclude the article in the last section.

## Related Work

The concept of the digital twin dates back to Grieves' presentation about product lifecycle management (PLM) in 2003, during which he proposed the concept of the digital twin creating virtual models of physical objects digitally and simulating their behaviors in a real environment [1]. Later, Glaessegen and Stargel proposed the most commonly used definition of the digital twin as follows: "Digital twin means the integration of complex products with multiphysics, multiscale, probabilistic simulation, and its function is to reflect the life of the corresponding twin." Therefore, a digital twin consists of three parts: the physical world, the virtual model in the virtual world, and the connection data that connect the two worlds [2]. The digital twin reflects the two-way dynamic mappings of physical objects and virtual models. Lee *et al*. proposed a five-level cyber-physical system (CPS) architecture for manufacturing systems based on Industry 4.0, supporting plug-and-play smart connections [3]. Dong *et al*. provided a deep learning (DL) architecture for a mobile edge computing system, where a digital twin of the real network environment was used to train the DL algorithm offline at a central server [4]. The digital twin computing module processes these data and informs the physical system about the discovered information, and it sometimes sends control commands to make necessary physical world changes or reconfigure system parameters [5, 6]. Chen *et al*. proposed a novel city cloud union architecture to handle the integration and provision issues in smart city [7]. Zhou *et al*. designed an iterative framework to resolve the data sparsity and inconsistency problems due to the user privacy-aware preferences [8]. The digital twin represents all the functions of its physical system in the virtual world. A system based on a digital twin can reduce damage or activate the self-repair mechanism, thereby increasing the possibility of successfully completing the task and extending the system life [9, 10]. The digital twin has developed from smart manufacturing and smart city, but it is limited to the application layer. How can we extend it to the network layer?

Digital twins promote the real-time monitoring, simulation, optimization and control of cyber-physical elements in cyber-physical systems. Cyber-physical systems based on digital twins can continuously acquire, integrate, analyze, simulate and synchronize product life cycle data across multiple stages and they also provide on-demand prediction services for different users in the physical space and cyberspace. In this process, the different tasks are efficiently executed and evaluated. Some emerging technologies, such as 5G and artificial intelligence (AI), can greatly promote the realization of digital twins in manufacturing systems [11, 12] In summary, AI brings self-awareness, self-adaptation, and self-configuration to the system functions and promotes the realization of digital twins. By learning operator/user preferences, priorities and the environment, digital twin-based observable systems are greatly enhanced. AI-empowered digital twins create new value, but they are still limited to the application layer.

Compared to digital twins in the application layer, Yu *et al*. [13] introduced cyber twins in the network layer which helped to solve fundamental network problems including network scalability, mobility and security. Based on Yu's work, we design intelligent service-oriented future network architectures based on cyber digital twins. We use a new cyber digital twin term in this article because it crosses multiple layers from the network layer to the application layer.

## Service and Resource Management Model

The cyber digital twin modeling layer realizes the realistic modeling of physical objects in cyberspace, and the data required for the modeling are obtained through the digital assets obtained by the communication agent function. Furthermore, the twin modeling layer realizes 3D scene modeling, spatiotemporal emergence and inference of complex information services in physical space. The required information is provided by the service analytical model, cross-space resource representation and management, and autonomous configuration of cross-space resources.

### Service Analytical Model

In future networks with cyber-physical space integration, the mappings from service to resource face considerable challenges. On the one hand, the continuous emergence of diversified scenarios makes service requirements more complex. Traditional mapping methods from service to resource are difficult to perform and may lead to low resource utilization. On the other hand, the introduction of physical space resources has greatly expanded the resource dimension that can be used to fulfill services and further increase the complexity of service mapping. In response to the above challenges, this article studies the service demand understanding model to divide complex service scenarios into scenes, which facilitates 3D scene modeling in the cyber digital twin modeling layer. Thus, realistic service scene emergence and spatiotemporal evolution of services are realized.

Based on the recent development of artificial intelligence models in the fields of target recognition and semantic transformation, service agents can automatically capture the network performance requirements of different services. Considering the continuous development characteristics of network service types and personalized service experience requirements, we adopt a multiagent learning mechanism to capture the heterogeneous service demands of multiple scalable agents. These multiple agents need to collaboratively learn and interact with each other in an environment. With multiagent RL, states become joint states of all the agents, and different rewards correspond to each possible joint action. Then, we transform the different service demands at the user level into cross-space resource requirements, including computation, storage, network bandwidth and cyber digital twins. The data and knowledge of physical objects are organized by cyber digital twin technology. According to the resource requirements, the network readily obtains the data and knowledge owned by the cyber digital twin. Considering service requirements and the dynamics of cross-space resources, a dynamic mechanism for the real-time updating of personalized network resource requirements is established.

## Cross-Space Resource Representation and Management

The resource layer across the cyber and physical space consists of unified cross-space resource representation and cross-space resource management.

**Unified Cross-Space Resource Representation:** As shown in Fig. 2, cross-space resources are complex, heterogeneous and dynamic. By integrating independent discovery, mappings and updates of cross-space resources, we establish a unified and complete cross-space resource expression, including:

- Forming a real-time multidimensional resource view
- Performing a visual analysis and multiangle presentation
- Supporting the efficient management of cross-space resources
- Providing decision-making for service.

By utilizing the built-in intelligent perception capabilities of the network architecture, an autonomous cross-space resource discovery mechanism is adopted. Based on the cyber digital twin expression model, the autonomous registration of physical space resource objects and the independent labeling of different resources are realized. Furthermore, considering the highly dynamic nature of resources, especially physical space resources, an independent update mechanism is introduced. A semantic model is established to understand the service requirement and extract semantic information from the service requirement. This semantic information is further converted from services to cross-space resources to facilitate cross-space resource management. The common data standard establishes a unified and complete resource expression across spaces to solve the resource heterogeneity problem. Multidimensional resource integration is carried out on this basis, and finally, a resource pool with independent update capabilities is generated, which provides basic support for cross-space resource management and control. With data analysis and visualization methods, we establish a multidimensional view of cross-space integrated resources. Furthermore, we support real-time and accurate resource monitoring, thus providing real-time resource status information for service decisions.

**Cross-Space Resource Management:** In traditional networks, network resource management is often based on current user needs, and systems passively allocate and manage resources. This resource allocation method is not only time consuming, but also causes resource shortages in the face of large demand requests. Therefore, this article proposes a resource intelligent management and control mechanism based on reinforcement learning (RL). In the cyber-physical converged network, we use reinforcement learning to establish entity mappings from the physical space to the network space. Through the study and analysis of the historical demand law of a specific object, we can accurately model the object and reasonably predict its possible future demand to realize the advanced allocation and intelligent management of resources. Thus, the problem of resource shortages during peak hours is alleviated, and the user's response delay is reduced.

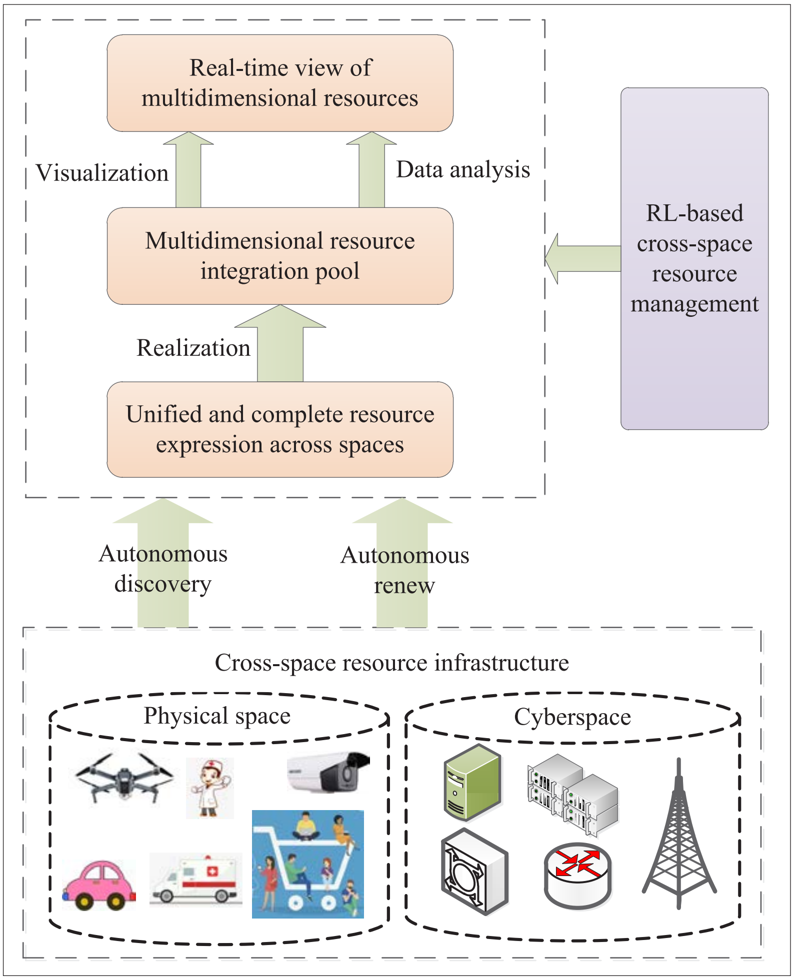


FIGURE 2. Cyber digital twin-based cross-space resource representation and management.

During the formulation of reinforcement learning, information such as the network environment and user needs is used as the input state of reinforcement learning, and resource management and control decisions are the outputs of reinforcement learning. According to different network optimization goals, we can formulate corresponding reward functions to guide and optimize the actions taken by agents. Under the guidance of the reward function, reinforcement learning can continuously optimize physical space object modeling and future state prediction. To make the decision-making of reinforcement learning more accurate and timely, we carry out certain pretraining beforehand and make the predictions more

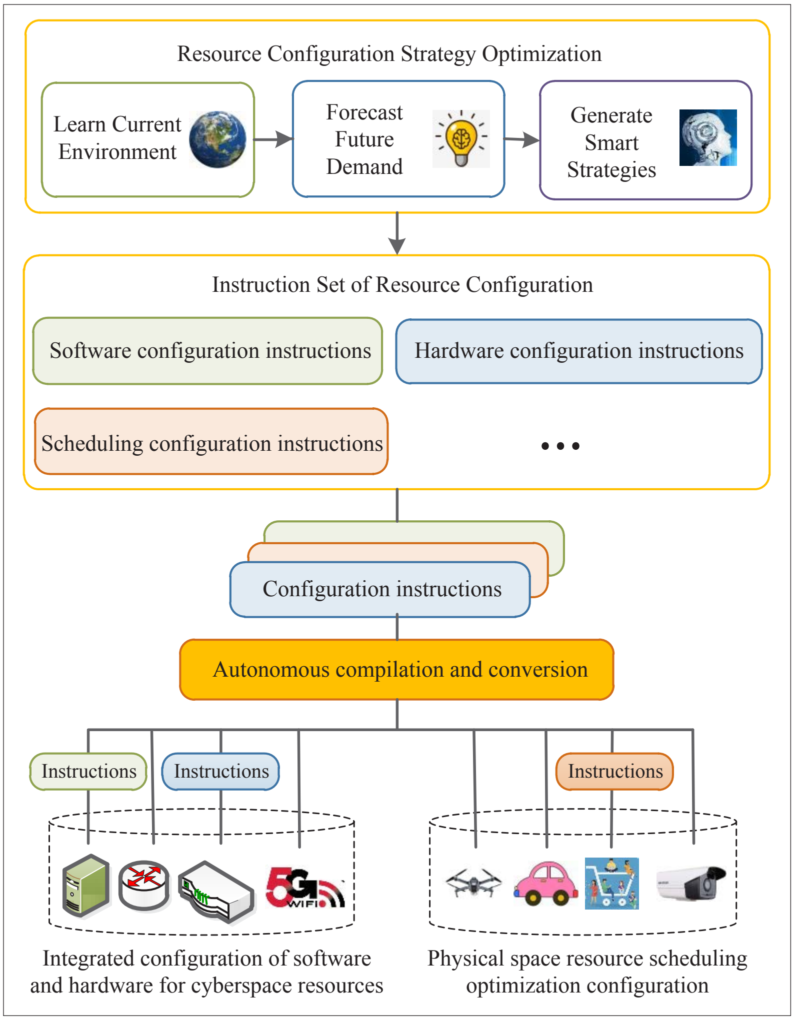


FIGURE 3. Autonomous configuration strategy of cross-space resources.

accurate during the application in the process of resource management and control.

## Autonomous Configuration of Cross-Space Resources

In the future network across the cyber-physical space, the large number of complex operations creates considerable challenges in resource configuration. By studying autonomous resource configuration across spaces, a comprehensive resource configuration strategy is established. Autonomous configuration is used to reduce human intervention and ensure the accuracy and efficiency of cross-space resource configuration. The autonomous resource configuration strategy is shown in Fig. 3.

To ensure cross-space resource configuration efficiency, a special configuration instruction set is defined to execute the optimized resource configuration strategy. In the specific configuration, the integrated software and hardware configuration of network resources and the optimal scheduling strategy of physical resources are comprehensively considered. They are combined with reinforcement learning to intelligently formulate a comprehensive configuration strategy for network and physical resources. Then, the required resources of the underlying network equipment and physical equipment are configured to meet the service requirements with appropriate network and physical resources.

The comprehensive resource configuration model adopts a top-down design. According to the needs of resource configuration, the grammatical rules of the resource configuration language are formulated. The required grammar is concisely defined, and the instructions are accurately expressed through structured expressions. Considering the complicated problem of cross-space resource configuration, artificial intelligence is introduced to help make intelligent decisions. To improve equipment utilization efficiency, reinforcement learning is adopted to learn the past equipment usage and the current environment and predict the equipment usage that may be required in the future. The proposed method makes the current equipment configuration decisions more reasonable by reducing equipment congestion and idleness, thus enabling efficient equipment use.

## RL-Based Resource Allocation Scheme with Cyber Digital Twins

We set up the cyber digital twin system in the core network to track user requests and coordinate the network and storage resources. To take advantage of the cyber digital twin, we propose a reinforcement learning-based (RLB) scheme to optimize the caching/pushing decisions and network transmissions.

Consider a general wireless communication network with a content provider, a core network, a base station (BS) and $K$ users. The core network has access to all $N$ files through the content provider and then transfers the files to the users through the BS. The BS can broadcast the files to all the users it covers. Additionally, the BS can cache files to relieve backhaul transmission, and we assume the cache capacity of the BS is $M$ files.

The whole system runs on an infinite time horizon, and the time is divided into slots, which are denoted as $t = 0,1,2,...$. At the beginning of each slot, the user can submit a request to the BS, and will be served before the end of the slot. We assume that the requests of each user evolve according to a certain pattern, and different users may have different habits. After receiving the requests, the BS checks its local cache to determine whether it can serve the user immediately or whether it needs to request the file from the core network. To make full use of the bandwidth when the network is idle, we introduce the push mechanism to transfer and cache files in advance. Our goal is to carefully choose which files are pushed and cached to reduce not only the average backhaul transmission but also the backhaul transmission peak. To achieve this goal, we define a transmission consumption function as $C(W) = e^W$, where $W$ indicates the transmission bandwidth including the pushing operation and the transmission request on the backhaul link. To minimize the time-averaged transmission consumption, we define the objective function as

$$\phi(\mu) = \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathrm{E}(C(W)), \tag{1}$$

where $\phi(\mu)$ is the time-averaged transmission cost and E is the expectation over user requests.

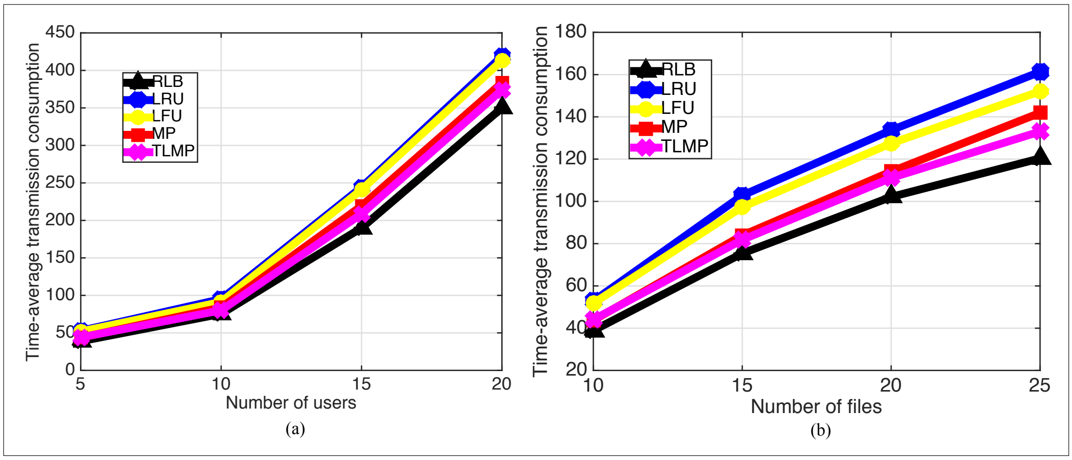


FIGURE 4. Comparison of time-average transmission consumption between the proposed RLB and other schemes: a) time-average transmission consumption under different numbers of users; b) time-average transmission consumption under different numbers of files.

RL can help build a model for each user and manage the caching and pushing operations properly. We formulate the user request process as a Markov decision process (MDP). The state of the RL model is the request of each user and the current cache state, the action is the caching and pushing decision, and the reward is the transmission consumption in each slot. Note that the new cached files are only from pushing or transmission requests. To compress the action space dimension, we use the differential between the previous and current cache contents to indicate the push action. To deal with the high dimensionality of the state space, we use a deep Q-network (DQN) as the RL policy. The inputs of the DQN are the requests of all users and the current cache state at the BS, and the output is the Q value of each cache decision.

RL can help build a model for each user and manage the caching and pushing operations properly.

## Performance Evaluation

We conduct experiments and simulations in terms of the intelligent control and management of network cache resources under the cyber digital twin model.

### Baselines

We compare the proposed RL-based scheme under the cyber digital twin model with the traditional cache replacement schemes and the joint cache and push schemes. The four related schemes are listed below.

**LRU and LFU:** Least recently used (LRU) and least frequently used (LFU) are the two most common cache replacement schemes that are widely used in practical applications. When the new file arrives, the LRU scheme replaces the least recently used file in the cache, and the LFU scheme replaces the file that is least frequently used.

**MP:** The most popular (MP) scheme is a caching strategy that uses the user request model as prior knowledge. According to the transition probability of user requests, it calculates the mathematical limit probability of each request, that is, the stable request probabilities of each file when the number of users tends to infinity. Based on the mathematical limit probability, the scheme selects the files that have the highest request probabilities.

| | |
|---|---|
| Number of users $K$ | 5 |
| Number of file $N$ | 10 |
| Cache size $M$ | 2 |

TABLE 1. The parameters settings of the simulation.

**TLMP:** The threshold local most popular (TLMP) scheme uses the Zipf-like distribution to model the long-term file popularity and establish the relationship between the former and the latter requests to capture short-term temporal information. Additionally, the scheme introduces the push mechanism. When the data transmission rate is below a given threshold, the scheme can decide to push the most popular content to make full use of the bandwidth.

### Simulation Results

We conduct the simulation with the parameters listed in Table 1, and we apply the same user request model as those in the related work [14]. The performance of the proposed RL-based scheme with the cyber digital twin and those of the other baseline schemes are shown in Fig. 4. The transmission consumptions of these schemes are compared under different numbers of users and files. Figure 4a shows the transmission consumption under different numbers of users. When the number of users increases, the number of requested files also increases, so the transmission consumption increases accordingly. Figure 4b shows the transmission consumption under different numbers of files. As the number of files increases, the accuracies of pushing and caching decrease. Therefore, the transmission consumption increases. The caching strategy becomes more important when the number of files increases. Therefore, the proposed RLB scheme shows more gains than the other schemes. In the figures, we can also see that the proposed scheme outperforms the other baseline schemes. It shows the performance of the proposed RL-based scheme under the digital twin and other baseline schemes.

We can profile each user in cyberspace, and the user requests in the future can be more accurately estimated according to the model, thereby achieving more efficient caching and network transmission.

We can see that the proposed scheme outperforms other baseline schemes under all circumstances. This gain is because of the help of cyber digital twins and reinforcement learning modeling. We can profile each user in cyberspace, and the user requests in the future can be more accurately estimated according to the model, thereby achieving more efficient caching and network transmission.

## Conclusion

In this article, considering the demand for developing future diversified information services, a cyber digital twin based future network service architecture is proposed to support new cross-space intelligent services and manage cross-space resources. The proposed network architecture consists of a service analytical model, cross-space resource representation and management, and an autonomous configuration model. Furthermore, an intelligent control and management method for cross-space resources under the cyber digital twin model is designed. The proposed method obtains an obvious gain by utilizing a comprehensive resource allocation model. The performance gain of the proposed RL-based scheme under a cyber digital twin is also analyzed. Due to space limitation, this article only presents a framework of intelligent service oriented cyber digital twin-based future network. Our future research will further generalize future network architecture and give more details about it.

## Acknowledgment

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