Metaverse for Wireless Systems: Vision, Enablers, Architecture, and Future Directions

Latif U. Khan, Zhu Han, Dusit Niyato, Mohsen Guizani, and Choong Seon Hong

Abstract

Recently, significant research efforts have been initiated to enable the next-generation — the sixth-generation (6G) — wireless systems. In this article, we present a vision of the metaverse toward effectively enabling the development of 6G wireless systems. A metaverse uses virtual representation (e.g., digital twin), digital avatars, and interactive experience technologies (e.g., extended reality) to assist analyses, optimizations, and operations of various wireless applications. Specifically, the metaverse can offer wireless system operations through virtual modeling that allows network designers, mobile developers, and telecommunications engineers to monitor, observe, analyze, and simulate their solutions collaboratively and virtually. We first introduce a general architecture of metaverse for wireless systems. We discuss key driving applications, design trends, and key enablers of the metaverse for wireless systems. Finally, we present several open challenges and their potential solutions.

Introduction

The term metaverse (https://www.thefastmode.com/expert-opinion/28940-exploring-the-metaverse-s-infinite-possibilities-with-6g) refers to a virtual model of a physical system that enables interaction of various entities, such as virtual models (e.g., avatars) of mobile devices/humans, virtual models of static entities (e.g., smart homes), and interactive experience technologies (e.g., augmented reality). Such a virtual modeling in the metaverse provides many benefits (e.g., analysis and real-time resource management) for wireless systems (e.g., sixth-generation (6G) wireless systems) by effectively enabling the design trends of proactive learning and self-configuring wireless systems [1]. The design trends of proactive learning and self-configuring wireless systems are necessary to meet the diverse requirements of wireless system applications (e.g., brain-computer interaction, smart tourism, and industry 4.0) in terms of traditional quality of service (e.g., latency and reliability) and quality of experience (e.g., sense of physical experience) metrics [2]. A self-configuring wireless system refers to an efficient operation with minimum possible intervention from end-users/network operators. A self-configuring design can benefit from a metaverse virtual model by performing extensive experiments. On the other hand, proactive learning [3] is necessary to optimally utilize network resources (e.g., computing, communication, and energy resources) in response to highly dynamic environments and stringent latency requirements. To perform proactive learning, there is a need to train metaverse models before users request services. These pre-trained models can be obtained using a privacy-preserving machine learning scheme, namely, federated learning (FL). Next, these pre-trained models will be stored and used by the metaverse to serve end-users. Collectively, a metaverse will enable self-configuring design and proactive learning in 6G to enable emerging applications.

The work in [1] proposed a digital twin–empowered architecture to address design challenges (e.g., self-configuration and proactive learning) of 6G systems. A digital twin uses a virtual model of the physical system together with classical approaches such as mathematical optimization, stochastic analysis, and machine learning for performance and cost optimization. Although a digital twin can offer several benefits and is effectively applicable to many applications, its use for wireless systems can face many issues, especially in meeting a variety of mobile service and application requirements. For instance, on one hand, a digital twin can be used to proactively and preemptively analyze a wireless system by using its virtual model. However, without incorporating the effect of mobile users or devices controlled by humans, for example, unmanned aerial vehicles (UAVs), within the virtual twin model, we may not be able to obtain results (e.g., estimating wireless channels or caching decisions at the network edge) that are accurate for actual physical systems. An overview of existing initiatives using digital twins and metaverse platforms, their limitations, and the role of the metaverse for wireless applications is shown in Fig. 1. In one way, software-defined networking (SDN) technology can be used for the efficient management of network functions. However, SDN cannot directly offer proactive, intelligent analytics and self-sustainability, and thus might not be able to meet the diverse requirements of emerging wireless applications and mobile users.

1 In this work, the keyword “proactive learning” refers to learning meta space models before user requests.

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In a metaverse-based system, one can use the concept of digital avatars that model human behavior. Likewise, other mobile devices (e.g., autonomous vehicles (AVs) and UAVs serving and/or loosely supervised by end-users) should also be represented by avatars (i.e., digital copies) in that they are related directly to humans. On the other hand, static entities and objects (e.g., roads, traffic signs, and buildings) should be included in the digital twin model, for example, they can affect wireless propagation and user mobility characteristics. Therefore, we will need to combine digital twins with avatars and interactive experience technologies in the metaverse to effectively model the physical world of wireless systems. For instance, consider accident reporting of cars and AVs. Roadside units (RSUs) and other objects in the environment can be represented by digital twins. The metaverse will capture the chaos that occurs if a real accident happens, for example, how people, AVs, and other cars react to the situation, in which abnormal and hotspot wireless traffic will be generated and mobility patterns will be observed. Accordingly, interactive experience technologies (e.g., augmented reality (AR), virtual reality (VR), extended reality (XR), and mixed reality (MR)) can be used by the metaverse to superimpose additional information on twin models and avatars in meta space. The information can be used by machine learning modules and/or human network administrators to analyze/control physical entities (e.g., UAV flying base stations and edge servers) for reporting accidents and other functions (e.g., lane change assistance and collision avoidance).

In the literature, a few works considered metaverse and its applications [3-6]. In [3], the authors presented the concept of a metaverse, recent advances, potential applications, and open challenges. The work also highlights social aspects and hyper spatiotemporal views that are important dimensions of the metaverse. The authors in [4] reviewed the role of artificial intelligence in the metaverse. They outlined six various technical aspects (i.e., neural interface, digital twin, networking, blockchain, machine vision, and natural language processing) toward the development of the metaverse. The authors in [5] surveyed the fusion of blockchain and metaverse as well as the recent advances. The work in [6] presented the role of 6G-enabled edge artificial intelligence for realizing metaverse. In contrast to the works in [3-6], this article focuses on an application of metaverse to wireless systems, that is, a metaverse-empowered wireless network. Note that there are two design aspects: wireless for metaverse, and metaverse for wireless. The wireless for metaverse deals with the resource management for efficient metaverse signaling over a wireless network [7, 8]. Our focus is on metaverse for wireless which deals with the use of metaverse for efficient resource management to enable various applications. We discuss the key enablers as well as key requirements of such a system. Furthermore, we present its architecture along with a wireless system example. The contributions of this article can be summarized as follows.

We present an overview and our vision of the metaverse toward enabling wireless systems. We are the first to identify the adoption of the emerging metaverse technology, and its potential to improve wireless systems and mobile services through the key enablers, such as interactive experience technologies, avatars, and digital twins.

Following our proposed concept of metaverse for wireless systems, we devise and introduce a general architecture to support its development. We highlight the main requirements that necessitate components and their connections presented in the architecture.

Finally, we present several future directions that require careful and holistic investigation, analysis, and designs to realize the proposed systems to achieve the full benefits.
Concept and Key Enablers

**Metaverse and Wireless Systems**

A metaverse of a wireless system will combine digital twins with interactive experience technologies (e.g., AR/VR/MR/XR) and digital avatars to replicate and actuate a physical wireless system [1, 6]. The first step in the creation of a metaverse is to virtually model (i.e., digital twinning) the physical scenario. The modeling can be performed by using various techniques, including mathematical modeling, simulation modeling, experimental modeling, and data-driven modeling. Next, additional information is superimposed (e.g., virtual objects in mobile environments) on the virtual model by using various sensing and monitoring techniques. Finally, digital avatars of humans are created in the metaverse to model the metaverse-based wireless system. The virtual model of the physical system can be designed using various techniques (e.g., mathematical modeling and experimental modeling). For mathematical modeling, generally, simplified assumptions (e.g., linear approximation for non-linear functions) are made. One can also use experimental modeling that is carried out by a series of experiments. However, there are some scenarios (e.g., wireless propagation in unconventional communications scenarios) that are inefficient or infeasible to be accurately modeled by mathematical modeling and even by experimental modeling [9]. To address this issue, data-driven modeling, which is based on training a machine learning model by using data generated, can be used [10]. Specifically, FL that uses distributed training can be used due to its privacy-preserving nature. Distributed training is based on training local models at devices and then sending the local models to the global aggregation server to obtain the global model. However, distributed training-based machine learning has a few challenges, such as non-independent and identically distributed (non-IID) data as well as device and network heterogeneity (i.e., the variable computing capacity of distributed training nodes). Note that FL can be used to model a wide variety of activities, such as avatar modeling, digital twin modeling, routing, wireless resource management, security, edge computing resource management, and mobility management, among others, in metaverse-based systems.

Other than virtual modeling for twins, avatars and interactive experience technologies are required for the metaverse. Examples of applications of MR are industrial plant maintenance and healthcare systems. XR covers all three interactive experience technologies, such as AR, VR, and MR, to make the digital world indistinguishable from the actual world. Additionally, XR provides us with seamless interaction among AR, VR, and MR. The key challenges of XR are interoperability and the design of interfaces for interaction among various interactive experience technologies.

Although interactive experience technologies use a virtual representation of humans as avatars in many scenarios (e.g., video games), in the context of a wireless system, novel digital avatars need to be designed that can produce realistic effects (e.g., due to wireless signal energy absorption, wireless signal reflection/refraction, and wireless signal attenuation) as actual humans. For instance, consider Terahertz (THz) communication which generally requires line of sight (LoS) communication. LoS communication

| Enabler                          | Key role                                      | Example in metaverse-based wireless system                                                                 |
|----------------------------------|-----------------------------------------------|------------------------------------------------------------------------------------------------------------|
| Interactive experience technologies | To annotate the virtual models for wireless system applications. | AR-based annotations for industry maintenance systems, VR/AR-based entertainment systems, XR-based research testbeds (e.g., Illinois Extended Reality testbed). |
| Digital avatars                  | To enable effects (e.g., mobility, signal loss) of humans of the actual world in metaverse. | Users in autonomous car models, mobile user models, and unmanned aerial vehicle models controlled by humans. |
| Digital twins                    | To virtually model the physical wireless system. | Base stations and their environment virtual model, smart factory model, and healthcare system model.      |

**TABLE 1.** Metaverse: Enablers, their key role, and wireless system counterparts.

Enablers

The key enablers of a metaverse are digital twins, digital avatars, and interactive experience technologies (i.e., AR/VR/MR/XR), and their roles and wireless counterparts are given in Table 1. These key enablers are in turn activated by various artificial intelligence (AI) schemes, computing, communication, digital modeling, sensing, and localization technologies. For a wireless metaverse, the first step is to create a digital twin of the physical wireless system. The virtual model of the physical system can be designed using various techniques (e.g., mathematical modeling and experimental modeling). For mathematical modeling, generally, simplified assumptions (e.g., linear approximation for non-linear functions) are made. One can also use experimental modeling that is carried out by a series of experiments. However, there are some scenarios (e.g., wireless propagation in unconventional communications scenarios) that are inefficient or infeasible to be accurately modeled by mathematical modeling and even by experimental modeling [9]. To address this issue, data-driven modeling, which is based on training a machine learning model by using data generated, can be used [10]. Specifically, FL that uses distributed training can be used due to its privacy-preserving nature. Distributed training is based on training local models at devices and then sending the local models to the global aggregation server to obtain the global model. However, distributed training-based machine learning has a few challenges, such as non-independent and identically distributed (non-IID) data as well as device and network heterogeneity (i.e., the variable computing capacity of distributed training nodes). Note that FL can be used to model a wide variety of activities, such as avatar modeling, digital twin modeling, routing, wireless resource management, security, edge computing resource management, and mobility management, among others, in metaverse-based systems.

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in THz communication will be affected by humans in real-time systems [11]. As another example, the concentration of red blood cells (RBCs) affects THz communication-based nanonetworks [12]. The path-loss and molecular noise decrease with an increase in the concentration of RBCs, and vice versa. Specifically, the human body's effects on THz communication are absorption, attenuation, dispersion, and scattering. The concentration of RBCs is proportional to the absorption effect of the blood for THz communication. Moreover, blood and its components can cause dispersion. Other than that, the high concentration of blood will cause more attenuation and vice versa.

**Metaverse-Based Wireless System Architecture and Use Cases**

**ARCHITECTURE**

**Implementation Aspects:** There are three main implementation aspects of the metaverse-based wireless systems, namely, implementations of the meta space, physical interaction space, and interfaces for the communication between the meta space and physical world, as shown in Fig. 2. A meta space can be implemented using an edge or remote cloud, depending on the application. For instance, autonomous car functions (e.g., accident reporting) may require instant computing power in a meta space. Therefore, meta space will be implemented using edge servers. On the other hand, a cloud can be used for the implementation of meta space for applications that are delay tolerant. Implementation of a meta space will require seamless interaction among digital twins, avatars, and interactive experience technologies. For the interaction between the meta space and physical space, wired and wireless interfaces can be used. Wired interfaces can use the backhaul links that connect edge devices with the meta space implemented at the remote cloud. On the other hand, the end-devices can be connected with the edge-based metaverse using a radio access network. Efficient multi-access schemes with effective resource allocation will be required for radio access networks for multiple metaverse-based applications. Wireless resources will be used for performing various tasks, such as the transfer of data, learning model updates, interactive experience technologies data, and control information. Also, metaverse-based applications must be isolated from each other for seamless, cost-efficient operation over the shared physical network resources (e.g., edge servers and wireless resources). Here, we discussed the implementation of the metaverse-empowered wireless system. Next, we will discuss various operations that could be performed using the proposed framework.

**Operation Aspects:** For a metaverse-based wireless system, there are three main operation aspects, such as training of meta space models prior to requests, online control of physical space entities, and end-user requests. Note that all these operations will take place simultaneously or at different times, depending on the scenario. For instance, FL is an iterative process and requires many rounds of communication between the meta space and the physical space. Meanwhile, if a user requests a service from the meta space, then the meta space will
perform online control along with offline training. Offline training for getting pre-trained meta space models prior to user request can enable proactive learning for efficient resource optimization. To do so, one can use various learning schemes: centralized ML and FL. For a metaverse-based system, FL can be preferably used due to its inherent feature of better privacy preserving capability and low communication resources requirement for taking into account the frequently generated data. For instance, autonomous cars generate 4,000 gigac bit of data every day, therefore, transferring the autonomous cars data to the centralized location for training a centralized ML model will consume significant communication resources. To address this issue, one can use FL that only sends local models (i.e., that have significantly lower size than the whole local dataset) to the edge/cloud server for aggregation as shown in Fig. 2. Next to getting a pre-trained model using FL, one can store the model using blockchain which will yield immutability and transparency.

Now, we discuss how to make a user request from a metaverse-based wireless system. A user can initiate a request that must be authenticated before processing it to prevent malicious users from accessing the system. Next to authentication, data synchronization must transpired wireless system. It is necessary to provide fresh data to the metaverse deployed at the network edge/cloud. Such data is needed for performing various tasks such as training machine learning models. For transferring fresh data to edge/cloud-based metaverse, there is a need to allocate dynamically wireless bandwidth. To efficiently carry out data synchronization, the work in [13] proposed a metaverse platform that hosts an infrastructure (e.g., UAVs) for collecting fresh data for multiple virtual service providers (VSPs). A set of UAVs with similar features is used for collecting fresh data for VSPs. To enable such interaction between VSPs and UAVs, effective incentive mechanisms are required to provide the UAVs with a proportional reward for their sensing tasks. Additionally, there is a need for dynamic resource allocation for performing sensing tasks. On the other hand, as shown in Fig. 3, semantic learning algorithms, prototyping, meta space, and physical space synchronization schemes must be secure, sustainable, and scalable. Scalability enables the efficient operation of a metaverse-based system for a large number of end-users without compromising the QoS. These requirements need to be fulfilled in addition to security for the effective operation of a twin-based system.

**Requirements:** For a metaverse architecture, general requirements along with relationships with each other are shown in Fig. 3. These requirements include synchronization between meta space and physical space data (i.e., fresh data for estimating digital twins and avatars parameters), accurate prototyping of digital twins (e.g., virtual model closest possible to actual physical scenario), scalability (i.e., energy-efficient operation), semantic reasoning efficiency (i.e., scenario-dependent learning models in wireless communication), security and privacy.

In metaverse-based wireless systems (an example scenario is shown in Fig. 4, there are two main challenges, namely, synchronization and accurate estimation. Synchronization refers to the data freshness between the meta space and physical space, whereas estimation deals with the accurate representation of digital twins and avatars in meta space. The states of the physical network vary significantly with time. For instance, consider a wireless channel and computing capacity for a certain task (e.g., AR-based industrial management) in the physical system. Other than accurate estimation, data synchronization is necessary for a metaverse-based wireless system. It is necessary to provide fresh data to the metaverse deployed at the network edge/cloud. Such data is needed for performing various tasks such as training machine learning models. For transferring fresh data to edge/cloud-based metaverse, there is a need to allocate dynamically wireless bandwidth. To efficiently carry out data synchronization, the work in [13] proposed a metaverse platform that hosts an infrastructure (e.g., UAVs) for collecting fresh data for multiple virtual service providers (VSPs). A set of UAVs with similar features is used for collecting fresh data for VSPs. To enable such interaction between VSPs and UAVs, effective incentive mechanisms are required to provide the UAVs with a proportional reward for their sensing tasks. Additionally, there is a need for dynamic resource allocation for performing sensing tasks. On the other hand, as shown in Fig. 3, semantic learning algorithms, prototyping, meta space, and physical space synchronization schemes must be secure, sustainable, and scalable. Scalability enables the efficient operation of a metaverse-based system for a large number of end-users without compromising the QoS. These requirements need to be fulfilled in addition to security for the effective operation of a twin-based system.

**Example Use Cases**

**Use Case 1: Metaverse-Empowered Wireless System:** Here, we present a use case of a metaverse-based wireless system as shown in Fig. 4. The physical space consists of small cell base stations, edge computing servers, hospitals, industries, mobile users, and a remote cloud. In the meta space, we need twin models of the physical counterparts, such as hospitals, industry, and base stations. Meanwhile, we will also need to design avatars that effectively model the actual users in the physical space. To give a more concrete example, let us consider an online support service for a remote monitoring application in an industry 4.0 scenario which is enabled by metaverse. To manage industrial tasks and faults, the remote live support system will consist of a twin deployed at the
network edge, a client with an integrated camera and operating system in the physical interaction space, and the remote expert. The client with a camera captures video and sends it to the twin at the edge server, where computationally expensive tasks occur. Then, the results are sent to the remote expert for further action. The remote expert adds annotations to the video using interactive experience technologies (e.g., XR) and sends them to the client for guidance regarding operation and fault removal. Another example use case can be a healthcare metaverse that combines interactive experience technologies with twins and avatars in the meta space to analyze/control healthcare equipment. Such a health metaverse can be used for medical education, training, and surgical procedures.

**Use Case 2: Network Virtualization for Metaverse**

To enable the efficient operation of a metaverse for wireless systems, one can use the concept of network virtualization, which enables the buying of resources (i.e., computing and wireless) from network operators and selling them to end-users through metaverse operators. The network operators sell wireless and computing resources and want to maximize their profit, whereas the end-users want to maximize their performance. From the perspective of end-users, one can define a cost function that accounts for wireless resource cost, computing resource cost, communication latency, and computing delay. There is a need to minimize the cost by optimizing the communication resource price, computing resource price, resource allocation, and computing resource management. On the other hand, one must ensure the network operators’ minimum acceptable profit by using constraints. The physical space in our network consists of a massive number of sensing nodes and mobile entities. These mobile entities are represented as digital twins in meta space. Since the sensing nodes are massive in number, we consider their distribution to be continuous [14]. Different from computing latency for digital twins, we use a distribution function and unit volumetric densities to compute the cost (i.e., latency) [15]. Additionally, we consider reliability in terms of the chance constraint that the outage probability must be less than a certain threshold for both sensing nodes and mobile entities. To carry out the above complex interaction, a metaverse operator will buy resources from the network operators and sell them to the end-users. To do so, we propose a scheme that uses convex optimization for computing resource management, communication resource cost management, and computing resource cost management. For resource allocation and association, we use a hierarchical matching approach that uses one-sided one-to-many matching for resource allocation and one-sided one-to-many matching for association. We use two baselines (i.e., baseline-RA and baseline-AS) for performance comparison. The baselines are different from the proposed scheme in that baseline-RA uses random association, whereas baseline-AS uses random association. Figure 4b1 shows the cost (transmission latency) vs. iterations for various schemes that reveal the performance enhancement of the proposed scheme over baselines. Similarly, Fig. 4b2 shows the overall cost vs. avatars and sensing units, which also reveals the performance enhancement of the proposed scheme over all baselines. Finally, we observe the cost vs. iterations for the proposed scheme by varying sensing intervals in Fig. 4b3. Figure 4b3 shows the stable nature of the proposed scheme for various sensing intervals. Different from the aforementioned figures, the baselines for Fig. 4b3 use equal assignment of cost for computing resources and wireless resources. Furthermore, equal computing resources are allocated for Fig. 4b3.
CONCLUSION AND FUTURE DIRECTIONS

We have provided a vision for a metaverse-based wireless system. The metaverse could be a promising technology for implementing 6G and beyond wireless systems. A set of key enablers for such a wireless system has been outlined. Additionally, we have proposed a high-level architecture along with an actual wireless system example for a metaverse-based wireless system. Several future directions for research are as follows:

META SPACE AND PHYSICAL SPACE SYNCHRONIZATION

How to achieve efficient and effective synchronization between the meta space and physical space? In a metaverse-based wireless system, the meta space should be synchronized (i.e., in terms of system states) well with the physical space. To do so, there is a need to propose a joint sampling and communication framework for the meta space. The purpose of sampling is to gather the system states (e.g., temperature data and vehicular data) in the physical space for use in the meta space. Note that sampling uses computing resources that have limitations at the end-devices. Therefore, one must propose a computationally efficient sampling scheme. Next to sampling, there is a need for efficient communication of the sampled data to the meta space.

To do so, we should propose quantization (i.e., to minimize the size of the transmitted data) and packet error rate minimization scheme while transmitting the quantized samples to the meta space.

BLOCKCHAIN-BASED SECURE DATA MANAGEMENT FOR METAVERSE

How to handle the distributed learning data sets and other data in a meta in a secure fashion? There is a wide variety of players in metaverse-based wireless systems who will need to interact in a secure manner. Handling distributed learning data sets and other data for metaverse-based systems will therefore require security, privacy, and confidentiality. Blockchains can be used for managing distributed meta data sets in an immutable and transparent manner. Additionally, computationally efficient consensus algorithms will be required for blockchains to handle meta-data distributed data sets in a scalable and sustainable manner. Consensus algorithms for metaverse should be designed such that they can offer a reasonable trade-off between scalability, sustainability, and computing delay. On the other hand, blockchain has privacy issues that must be resolved. These include homomorphic encryption, ring signatures, and confidential transactions using cryptographic schemes.

PROTOTYPING

How to prototype the avatars and digital twins for metaverse? In a metaverse-based wireless system, effective modeling of digital twins and avatars in a meta space is challenging. For modeling avatars, there is a need to model physical users’ parameters (e.g., mobility and 3D shape). For mobility, deep learning can be used to predict the mobility patterns of avatars. Additionally, the modeling/estimation of digital twins states in the meta space for the wireless system static entities will be required. For instance, modeling of the base stations and the wireless propagation channels in meta space can be performed using mathematical modeling, experimental modeling, or data-driven modeling (i.e., training a machine learning model). While data-driven modeling can be more effective than the other techniques, it may incur high training costs. Therefore, low-complexity machine learning models will be desired for twin modeling.

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