Integration of Sensing, Communication and Computing for Metaverse: A Survey

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The metaverse is an **Artificial Intelligence (AI)**-generated virtual world, in which people can game, work, learn and socialize. The realization of metaverse not only requires a large amount of computing resources to realize the rendering of the virtual world, but also requires communication resources to realize real-time transmission of massive data to ensure a good user experience. The metaverse is currently moving from fiction to reality with the development of advanced technologies represented by AI, blockchain, extended reality and **Digital Twins (DT)**. However, due to the shortage of communication as well as computing resources, how to realize secure and efficient data interaction between the virtual and the real is an important issue for the metaverse. In this article, we first discuss the characteristics and architecture of the metaverse, and introduce its enabling technologies. To cope with the conflict between limited resources and user demands, the article next introduces an **Integrated Sensing, Communication, and Computing (SCC)** technology, and describes its basic principles and related characteristics of SCC. After that, solutions based on SCC in the metaverse scenarios are summarized and relevant lessons are summarized. Finally, we discuss some research challenges and open issues.

CCS Concepts: • **Networks** → **Ad hoc networks**; • **General and reference** → **Surveys and overviews**; • **Human-centered computings** → **Ubiquitous and mobile computing**.

Additional Key Words and Phrases: Metaverse, sensing, communication and computing integration, digital twins, edge computing

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1 INTRODUCTION

As a new paradigm for the next-generation Internet, the metaverse aims to create a virtual space parallel to the real world, where people communicate through digital bodies as they do in the physical world [14]. Due to the emergence of the metaverse, researchers have been studying it and defining its concepts. Unfortunately, researchers are still unable to find the exact shape of the metaverse and its boundaries [119]. Generally, the metaverse can be regarded as a binary world, where both physical and digital virtual worlds merge. When it comes to spatio-temporality, the metaverse is a digital world that is virtual in the spatial dimension and real in the temporal dimension; when it comes to independence, the metaverse is a virtual world that is closely linked to the physical world but with high independence; when it comes to authenticity, the metaverse has digital bodies of real-world objects and digital products that are uniquely its own. Similar to the movie "Top Gun", people enter the virtual space through Virtual Reality (VR) devices as digital bodies, trade and create things in the virtual space. It has an impact on the physical world through the influence of people's thoughts, and even changes people's behaviors in the physical world. To realize this dualistic world, the metaverse goes through three successive stages from a macro perspective [35]: (i) Digital Twin (DT), (ii) digital native, and finally (iii) surrealism. The first stage is to generate a mirror world corresponding to the physical world, consisting of high-fidelity DTs of people and objects in the physical world. Various attributes (user activities and emotions) in the virtual world are a high degree of simulation of physical objects. The second stage focuses on the creation of the local content in the virtual world. People can participate in the creation of virtual worlds in the form of digital avatars, which can inversely influence the physical world. In the third stage, the meta-universe can form a self-sustaining and persistent hyper-real world. The virtual world and the physical world can be seamlessly integrated. The physical world becomes a subset of the virtual world, and the virtual world produces things that do not exist in the physical world. The current development of metaverse is in the budding stage (i.e., DT stage), so the discussion of metaverse in this article is mainly focused on the first stage.

Current Internet of Things (IoT) technology is developed rapidly and our life is filled with a variety of sensors for information collection. The development of 5G and beyond 5G networks has increased the rate of information transfer among nodes. Artificial Intelligence (AI) has also shown great potential for data processing and analysis. The metaverse, as a mirror of the physical world, requires real-time mapping of information from the physical world to the virtual world through DT technology. Correspondingly, communication networks need to have the ability of intelligently sensing the physical world and maping the virtual world everytime and everywhere [120]. The current proliferation of wireless communication and sensing devices makes the contradiction between the endless growth of service demands and the limited wireless resources particularly prominent, and the current wireless network architecture and related technology cannot meet the development needs of the metaverse.

The Integrated Sensing, Communication, and Computing (SCC) network is a network with simultaneous physical and digital space sensing, ubiquitous intelligent communication and computing capabilities. Collaborative sharing of resources can be realized through integrated communication-sensing-computing devices, thus supporting the implementation of various applications in the metaverse. As mentioned in [31], the platform architecture of the metaverse can be divided into the following layers (as shown in Fig. 1):

- Infrastructure: consists mainly of 6G, cloud data centers and graphics processing units;
- Human-computer interaction: mainly enabled by wearable devices, mobile devices, haptics, sound recognition systems and neural interfaces;
- Decentralization: mainly enabled by the blockchain and Edge Computing (EC);
- Spatial computing: mainly enabled by 3D engines, VR, Augmented Reality (AR) and eXtended Reality (XR);
- Experience: mainly consists of gaming, socializing, esports, shopping, events, festivals, work and study.

We can discover that the application of SCC is extensive and diverse. For example, during data processing, SCC allows for fast channel selection and low transmission latency. In addition, SCC can assist accurate speech

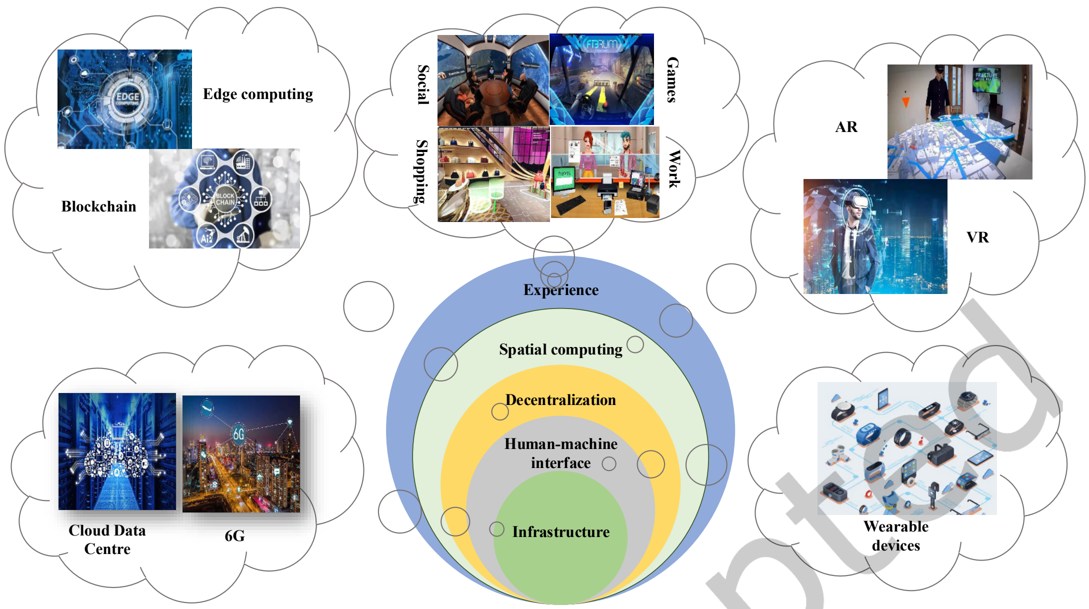


Fig. 1. The metaverse platform architecture.

recognition and other language processing to optimize human-computer interaction. It can also improve the visual experience in the metaverse by enhancing AI's ability through multidimensional perception and ubiquitous communication. Overall, SCC can make people's experience in the metaverse realistic through the fusion technologies, multidimensional perception of various information in the physical world, ubiquitous computing and communication capabilities.

1.1 Prior Related Surveys

With the introduction of the metaverse concept, there are many researchers who have summarized different aspects of the metaverse. A technical framework for a metaverse in terms of infrastructure, management, basic public technologies, social networks, and virtual reality is presented in [69]. Authors in [35] review the relevant technologies of the metaverse and propose a framework for the metaverse. *Cheng et al.* [14] review the research progress made by major technology companies towards the metaverse and existing virtual reality platforms. The applications of EC in the metaverse are surveyed in [120] and [115]. The former focuses on the integration of EC with the metaverse infrastructure, while the latter concentrates on the impact of combining EC and the blockchain in the metaverse. Authors in [31] and [119] focus on the application of AI and technical details related to how AI and the blockchain can be integrated with the metaverse. Two articles, [138] and [106], discuss privacy and security issues and related countermeasures in the metaverse. Authors in [106] summarize current issues concerning authenticated access, socializing, data management, and economic aspects arising from metaverse applications, and summarize current state-of-the-art approaches to address these issues. This article focuses on the application of SCC technology in the metaverse. The current key technologies for implementing the metaverse based on SCC are summarized, and the corresponding solutions are summarized according to different application scenarios in the metaverse. The comparison between this article and related surveys is summarized in Table 1.

Table 1. Comparisons of related surveys.

Focus	Ref.	Contribution
General framework	[69]	• Described the technological framework of the metaverse in terms of infrastructure, management, basic technologies, social networks and virtual reality.
	[35]	• Discussed techniques related to the underlying metaverse and proposed an overall framework for the metaverse.
EC	[120]	• Discussed the convergence of EC and metaverse infrastructure.
	[115]	• Discussed the application of EC and blockchain in the metaverse.
AI	[31]	• Discussed the application of AI in the metaverse.
	[119]	• Discussed the application of AI and blockchain in the metaverse.
Privacy security	[138]	• Discussed security and privacy issues existing in the current metaverse from the perspectives of information, communication, scenarios and commodities.
	[106]	• Discussed privacy and security issues in the metaverse from seven aspects: identity, data, network, economy, governance, and the impact of physical society.
SCC	This article	• Discuss the role of SCC technologies, formed by the integration of communication, sensing and computing technologies in the metaverse. • Discuss the application of four technologies, including AI, 6G, EI and blockchain, which facilitate the implementation of SCC in the metaverse. • Summarize solutions including different scenarios, in smart home, smart factory, medical health, intelligent transportation, UAV and space-air-ground integrated networks in the metaverse.

1.2 Contributions

This article focuses on SCC in the metaverse, and the specific contributions are summarized as follows:

- We initially introduce the relevant properties and the architecture of the metaverse. Then, we discuss the enabling technologies including 6G communications, Edge Intelligence (EI), DT and blockchain, which can provide strong supports for the realization of the metaverse from aspects of communication, computation, virtual-reality mapping and security.
- We discuss SCC and its characteristics by revealing its primary role for enabling technologies to meet the current needs of the metaverse.

- We detail six typical application scenarios and summarize corresponding SCC solutions in the metaverse from both local and open space and provide learned lessons.
- By investigating the application of SCC in the metaverse, we outline some challenges and future research opportunities correspondingly.

1.3 Structure

The rest of the article is organized as follows. The basic features and characteristics of SCC are described in Section 2. Key technologies for the implementation of SCC are presented in Section 3. In Section 4, we summarize solutions for open space and local space scenarios in the metaverse. In Section 5, we discuss open issues and potential research directions for SCC in the metaverse. In Section 6, we summarize this article systematically.

2 ARCHITECTURE AND ENABLING TECHNOLOGY FOR METAVERSE

As a kind of virtual world mapped by the real world, the metaverse needs a huge amount of data from the physical world for realization. Secure and reliable transmission of massive data between the physical world and the virtual world is the basis for the realization of the metaverse. Traditional communication, computing and encryption technologies can not satisfy the requirements of transmission rate, reliability and security in the metaverse. With the development of 6G, blockchain, DT and EI technologies, the realization of metaverse becomes a reality. This section introduces the metaverse architecture and the enabling technologies for the realization of the metaverse.

2.1 Metaverse Architecture

With the rapid development of communication, computing, AI, and security technologies, the meaning of metaverse is constantly expanding. On one hand, the metaverse can be a kind of parallel universe of the physical world, providing users with an immersive experience. On the other hand, the metaverse can be the fusion and interaction of the virtual world and the physical world. Therein, the things in the real world can be synchronized to the virtual world, and the behaviors of human beings in the virtual world have corresponding impacts on the physical world. The ultimate development of the metaverse is a new type of world, in which the physical world and the virtual world merge and interact, i.e., the "integrated world".

As shown in Fig. 2, as a world where the virtual world and the real world merge, the metaverse mainly consists of the physical world, the virtual world, and the enabling technologies that support the interaction between the virtual and the real. Each stakeholder in the physical world controls the components that affect the virtual world. Stakeholders can make an impact in the virtual world, and the impact provides feedback to the physical world. The main stakeholders are:

- Users: They can immerse themselves in the virtual world by wearing devices such as head-mounted displays or virtual reality goggles through their digital bodies. In the virtual world, users can interact with others' digital bodies by manipulating their own digital bodies.
- IoT sensors: They are deployed in the physical world, and maintain as well as update the virtual world with the information collected from the physical world. For example, DT models of physical entities are realized based on the acquired physical world-aware data. Current wireless sensor networks are independently owned by sensor service providers, which can provide real-time sensory data to virtual service providers to generate and maintain virtual worlds.
- Virtual service provider: Its major focus is on the development and maintenance of the metaverse. Similar to YouTube, the metaverse prefers to enrich itself with user-generated content such as games, art and social applications. This user-generated content can be created, traded and consumed in the metaverse.

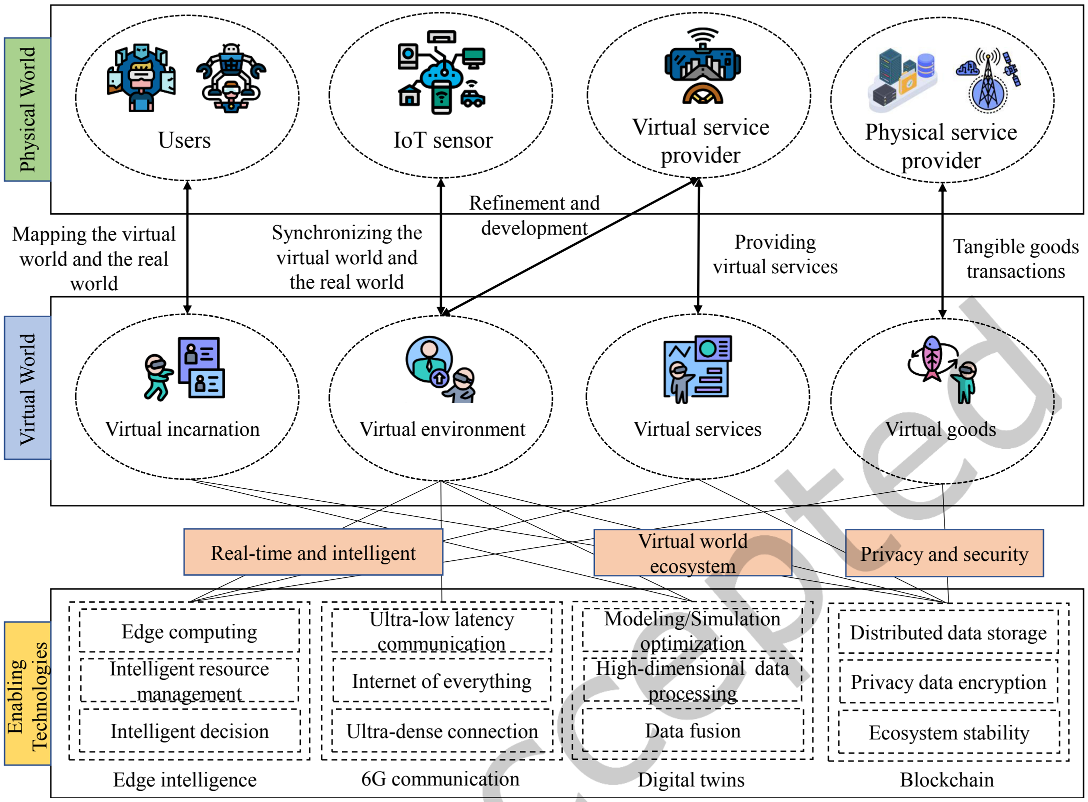


Fig. 2. The brief architecture of metaverse.

- Physical service provider: It operates the physical-world infrastructure to respond the operations in the virtual world. These operations include not only the invocation of computing and communication resources at the network edge, but also specific transactions in the physical world for payments made in the metaverse.

The realization of such a fusion world requires not only a large amount of data from the physical world, but also advanced technologies to support. It starts with creating a virtual world that can interact with the physical world synchronously, i.e., the things in the real world need to be mapped in the virtual world, and thus a large quantity of computing resources are required. Although cloud computing is powerful, information needs to be uploaded to the remote server for processing. It can not meet the low-latency requirement of the metaverse, and a computing paradigm, that is closer to the source of the generated information, is imperative. As the integration of Artificial Intelligence (AI) and Edge Computing (EC), Edge Intelligence (EI) can provide users with intelligent decision making and flexible support at the network edge, to cope with the requirements of the metaverse.

Furthermore, the realization of the immersive experience in the metaverse requires real-time massive data interactions between physical and virtual worlds. Current communication technologies can not meet the requirements of throughput, latency, and connection density in the metaverse to achieve a fully intelligent network that can provide an immersive experience for users [68]. 6G communication is promising to provide ultra-dense connection, ultra-low latency communication, and ultra-high network throughput, which is a key technology to cope with the performance requirements in the metaverse. The ultimate realization of the metaverse is that physical and virtual worlds can be integrated to interact with each other, requiring the mapping and interaction between them. DT can map information from the physical world to the virtual world for processing. By integrating with AR, VR and XR technologies, it can realize the mutual mapping of virtual and reality things.

The metaverse not only generates a large amount of user privacy data, but also constructs its own economic system and related laws and regulations. Therefore, ensuring data security and stability as well as efficient operation of the economic system in the metaverse requires secure data sharing technologies. Blockchain, as a secure and efficient distributed data sharing technology, can not only ensure data security in the metaverse, but also achieve stability, efficiency, transparency and certainty in the operation of economic systems in the metaverse.

In summary, the implementation of metaverse places high requirements on the communication and computing, the mapping between virtual and physical worlds, and privacy and security technologies. In order to address these requirements, the rest of this section provides a detailed introduction to the corresponding technologies in the metaverse, including 6G communication, EI, DT, and blockchain.

2.2 6G Communications

The realization of the metaverse requires real-time interaction of massive data between the virtual world and the real world to provide users with high-quality virtual and real interaction. The vision of metaverse is to realise a virtual world that is highly consistent with the real world. The user can perceive this virtual world not only visually and auditorily, but also through other senses such as touch and smell. The metaverse not only puts high requirements on data transmission latency and throughput, but also needs to enable data interaction among multiple sensors. However, current 5G and B5G technologies cannot meet the metaverse requirements, such as throughput, delay and connection density [22].

In contrast to the 5G network, the 6G network produces dramatic changes in the main KPLs. It has Tbps-class peak speeds, 10 to 100 Gbps experience rates, sub-millisecond latency, ultra-high throughput (up to 1Tb/s throughput), ultra-large connection density (up to 10^7devices/km^2), and can also provide stable communications for moving objects with speeds over 1000km/h [86]. The rapid growth of wireless traffic is driving the demand for high spectrum for wireless communications. In order to achieve wide coverage, mobile infrastructures prefer low frequency bands for network upgrades, which is prompting wireless technologies to develop new frequency bands for network upgrades [23]. To address these issues, 6G not only uses millimetre-wave spectrum, but also uses terahertz and even the visible spectrum, promising the first use of year-round spectrum for extreme connectivity. 6G has two application scenarios of AI and perception, which can not only sense and transmit various environmental information, but also sense people's sensory and emotional information, establish the interconnection of everything, and provide prerequisites for the realisation of SCC [32], which makes 6G cross the "People Connectio" and "Thing Connection", and move towards the Internet of everything. The current generation and development of Intelligent Reflective Surface (IRS), multiple access and beam assigment technologies enable wireless interactions for both line-of-sight and non-line-of-sight users, providing communication support for metaverse users to realise the immersive experience.

Based on characteristics such as ultra-low latency, high energy efficiency, and ultradense connectivity, 6G communications are currently being used by researchers in a variety of scenarios. To ensure the rapid establishment of user channels in highly dynamic and time-varying channel scenarios such as IoV, 6G and sensing technologies are combined to quickly acquire the channel state, and AI algorithms are used to reduce the noise of the collected channel information and predict the beamforming weights to achieve phase synchronisation [124]. This improves the throughput of multi-vehicle collaborative message transmission, and message transmission reliability and distance. By applying 6G communication technology to UAV scenarios and utilising MIMO and terahertz band communications, the UAV's movement trajectory design can be jumped from 2D to 3D, and

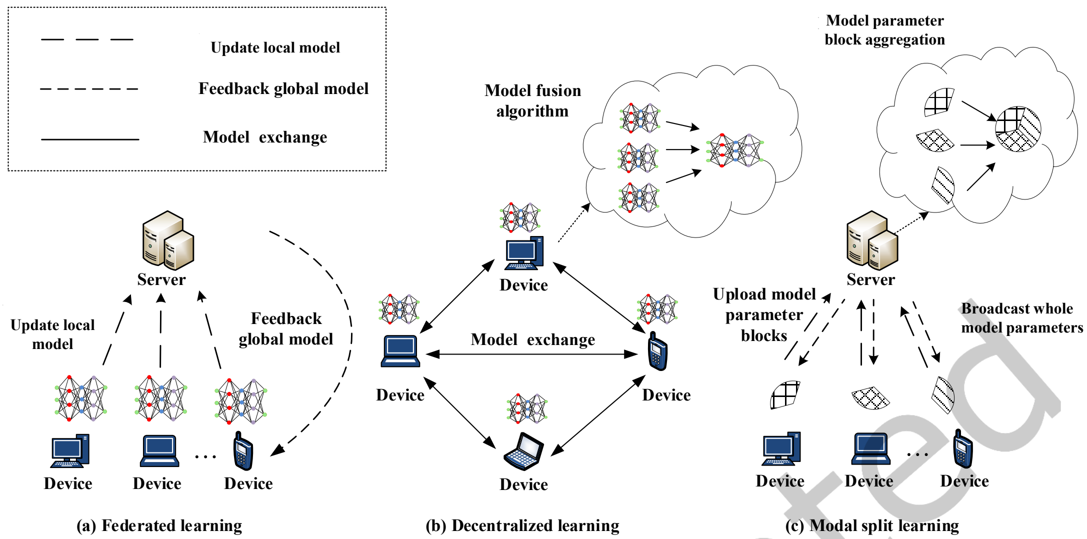


Fig. 3. EI models and architectures.

multi-UAV collaborative information transmission can be also realised [6]. 6G communication technology and Space-Air-Ground Integrated Network (SAGIN) framework are combined to achieve ubiquitous communication coverage by intelligent communication and effective allocation of heterogeneous network resources [127].

Overall, 6G communication provides a strong support for information interaction between the physical world and the virtual world. In addition, 6G communication also brings security risks. How to ensure that 6G communication can achieve safe and reliable data interaction between the virtual world and the real world is an interesting topic.

2.3 Edge Intelligence

EI refers to the integration of AI with Mobile Edge Computing (MEC) technologies, which presents possibilities for the implementation of current computation-intensive AI applications [51]. The metaverse, as an immersive virtual world, requires data transmission with ultra-high throughput and ultra-low latency to allow for a realistic experience. Traditional cloud intelligence requires endpoints to transmit data to the cloud when training the learning model, which can lead to significant latency, energy consumption, network congestion and privacy and security issues. Thus, cloud computing architectures are unable to realize the vision of "intelligence everywhere" [96]. Close to users and easy to deploy, edge servers such as cellular base stations and wireless access points can provide cloud-like computing resources at the network edge, which can compensate for the limited computing resources of mobile devices.

EI allows the acquired data to be transmitted to the edge server, and perform training and inference of EI models at the network edge. Depending on ubiquitous computing resources at the network edge, low-latency and highly reliable EI services can be realized by using fewer computing, communication and storage resources compared to cloud intelligence [82]. By nesting the training of AI models at edge nodes, there is no need to upload large amounts of data to the cloud. As a result, EI can help to reduce network congestion and energy consumption [36].

The training of EI models typically involves a loss function and a global model. By considering dynamic communication and computing environments when training models for EI, efficient distributed algorithms are required. As shown in Fig. 3, based on data and model partitioning principles, current edge learning models can be divided into three categories, i.e., Federated Learning (FL), decentralized learning and model split learning [36].

- FL is a collaborative ML algorithm that allows users to collaboratively train learning models on the edge nodes, and then integrates them to form a global model on a dedicated edge server without accessing users' private data [48]. As shown in Fig. 3(a), different edge nodes use their own private data for model training, and then upload the trained parameters to a dedicated server for model fusion. After that, the server feeds back the updated parameters to edge nodes.
- Decentralized learning utilizes peer-to-peer communication to enable the training of global models. As shown in Fig. 3(b), different users train models based on their own data, share them with adjacent nodes, and then integrate their trained models with the pre-nodes' models to form the global model.
- Model split learning enables a collaborative learning process by dividing the model parameters across edge nodes. As shown in Fig. 3(c), each edge node, including the edge device and the edge server, is responsible for training their own part of parameters, which are then uploaded to the edge server for global model construction. After that, the global parameters are fed back to the node for training.

Based on its strengths, EI can be used in industrial Internet [79], smart city [100], healthcare [71], Intelligent Transportation System (ITS) [72, 102, 113], UAV networks [101], wireless powered MEC [49, 97, 98, 100], AR/VR, etc. For example, EI can provide low-latency data processing for the smart city where massive amounts of IoT data are generated [45]. In healthcare, EI can enable applications that require ultra-low latency, such as remote medical care and remote surgery. EI can also achieve intelligent decision-making at the network edge, which greatly reduces the occurrence of accidents in ITS, and also improves the user experience of the metaverse.

2.4 Digital Twins

As a virtual world created by AI, how to map objects in the physical world to the virtual world is one important issue. DT is a multi-disciplinary, multi-physical quantity, multi-scale simulation system, allows objects from the physical world to be mapped in the virtual world by using data captured by sensors, and can have an impact on the physical world by using these real data in the virtual world for calculation and training [89]. At present, there are many studies on DT. It is considered to be a system that enables a reciprocal symbiosis between the physical world and the virtual world, and can evolve itself (i.e., self-adaptive, self-regulating, selfmonitoring, and self-diagnostic) by synthesizing other research on DT [66] and the requirements for metaverse implementation.

The goal of DT is to map the information in the physical world to the virtual world, and then use the collected multimodal data in the virtual world to approximate the various objects and environments in the physical world, and ultimately assist the physical world to make relevant and correct decisions and judgements [15]. There are several important enabling technologies for DT, including ML, cloud, fog and edge computing, AR and VR. Among them, ML acts as the foundation and brain of DT, using which the data mapped into DT can be quickly and effectively integrated, not only to optimise the virtual world mapping of DT [142], but also to make effective decisions about the relevant domains [122]. Since DT mirrors an entire complex range of systems, it requires massive amounts of computing resources [15]. The use of cloud, fog and edge computing technology can make use of computing resources of all layers and provide sufficient resource support for the implementation of DT. VR and AR technologies enable the interaction of the virtual world with the physical world. VR is achieved by simulating a virtual world to provide people with an immersive experience [11].

Taking the advantage of breaking the time dimension limit in the virtual world and the powerful computing resources in the DT platform, it is possible to realise real-time analysis and decision-making of the physical world data uploaded to the DT. Based on real-time sensing and data analysis capability, DT can enable efficient resource allocation [21] and quality inspection [52] for smart factories. It can also provide an emerging architecture for the industrial Internet [59, 60, 85], by combining DT with edge computing to make intelligent decisions.

Applying DT to healthcare can provide a new type of medical system [19] that can assist medical staff in treating patients, by identifying problems in a timely manner based on real-time information as well as relevant historical information. By applying DT to highly dynamic scenarios such as ITS and UAV networks, intelligent terminals can obtain information related to future systems with the help of powerful computing, communication and control capabilities [47]. DT can also enable collaboration among participants [30, 47, 133] to improve the utilization of system resources, predict the movements of participants in ITS and UAV networks [63, 94], and timely adjust participants' paths, speeds and other attributes to effectively avoid safety problems. Although DT has many applications, it is still in the theoretical stage, and the real-life applications for DT still need to be explored.

2.5 Blockchain

The realization of the metaverse requires the data support of massive terminals and sensors. These data contain information about the surrounding environment and personal data of the provider. Without data protection, serious security and privacy issues can be caused. Therefore, how to ensure the privacy and security of metaverse data and realise the endogenous security of metaverse is currently a hot topic of research. Blockchain technology is a data structure that preserves digital transaction records, also known as distributed ledger technology [3]. In a blockchain, the data is organized into a growing list of hash-chain ledgers that have been timestamped and verified by consensus operations [99, 105]. Through the design of hash chain blocks, consensus algorithms and smart contracts, blockchain technology can ensure the robustness of the metaverse. According to different application scenarios, blockchain is further divided into: public blockchain, federated blockchain and private blockchain [56]. Blockchain can be also classified into permissionless blockchain and permissioned blockchain based on different trust building methods [146]. The permissionless blockchain is a completely open blockchain where any user can participate in the network. Permissioned blockchain is a semi-open blockchain where only users who have been given something or recognised can participate in the network. Both federated blockchain and private blockchain belong to permission blockchain. Due to the special structure of blockchain and the adoption of technologies such as consensus mechanism and smart contracts, blockchain technology has the following characteristics:

- Decentralization: Transactions in the blockchain are verified, transmitted and managed based on individual nodes. They are stored in a distributed manner without the need for jurisdiction and identity verification provided by third-party institutions. This can significantly reduce the cost of services and the risk of single points of failure.
- Immutability: Due to the hash chain structure of the blockchain, any modification to any block in the blockchain invalidates all subsequent blocks. In addition, once the blockchain is formed, the data in the block can not be changed.
- Traceability: All kinds of data collected, shared and transmitted throughout the lifecycle of an IoT service are recorded in the blockchain, inherently providing traceability of trusted information.
- Transparency: Any entity involved in the blockchain can access and publicly verify transactions and the global state of the blockchain.
- Interoperability: The blockchain is a public or semi-public information platform, and can provide uniform access rules for data, breaking down traditional technical barriers for individual entities.

Based on the above characteristics, the information of end devices, transmission data, processing data and digital transactions in the metaverse can be inscribed in the blockchain in the form of transactions and without the inclusion of third-party institutions [145]. This can significantly reduce the cost of services and also ensure the traceable, reliable, non-tamperable, and non-repudiation nature of information and transactions. With the development and advancement of technologies, some latency-sensitive applications and scenarios can be implemented in the metaverse, where the traditional blockchain technology is unable to process massive amounts of data with low latency. To cope with the above problems, off-chain computing techniques have been proposed and studied. The authors in [121] leverage idle network computing resources for off-chain computing to process computationally intensive and latency-sensitive task executions. The authors in [132] increase the blockchain's scalability and achieve high-throughput data transactions by moving on-chain transactions off-chain. In addition, the blockchain can permanently track node behaviors through cryptographic evidence, especially for the supply chain, thus promoting a fair, transparent and auditable environment and preventing the misuse of personal data. Based on its outstanding features described above, the blockchain can not only keep data security and privacy, but also ensure that relevant laws and regulations of the future metaverse can be implemented in a fair and just manner. Currently, blockchain is widely used in smart industry [60], smart transportation [3], healthcare [55], smart grid [70] and other scenarios.

3 SCC TECHNOLOGY FOR THE METAVERSE

Due to the performance requirement of metaverse, the implementation complexity of techniques described above, and the limitations of existing wireless network resources [43, 78], one-dimensional resource optimisation does not work well. For example, in the environment with the heterogeneous network structure and time-varying channel conditions, reliable and stable interactions among nodes need to sense the channel and the surrounding environment state, and fuse the relevant environmental information for real-time channel modelling [32]. In the case of computation-intensive tasks and heterogeneous network resources, efficient utilization of computing resources and real-time processing of computing tasks not only require a reasonable match between the amount of computing tasks and computing resources, but also require real-time channel modeling through the perception of environmental information to cope with time-varying environments [28, 116]. Thus, SCC is the foundation for the above technologies, which can meet the requirements such as ultra-low latency, ultra-high throughput and ultra-density connections through joint allocation of sensing, communication, and computing resources in the network.

3.1 The Integration of Sensing and Communication

With the rapid development of IoT, the number of IoT devices is growing exponentially, which makes the spectrum congestion problem become a major issue for the implementation of metaverse. Limited bandwidth resources and the rapidly growing number of IoT devices are driving the development of Integrated Sensing and Communication (ISAC) technologies [137], which combine sensing and communication signals, and allow them to share the same waveform, spectrum, wireless infrastructure, and RF hardware, etc. Thus, ISAC not only improves spectrum utilization and alleviates spectrum scarcity, but also avoids the high cost of building dedicated wide-area sensing infrastructure and helps to unlock the maximum potential of cellular networks [110] [108].

There are currently two major approaches for ISAC: radar-communication coexistence and dual-functional radar-communication. The former designs radar sensing and communication as two separate systems with their own waveforms, separate transmitters and receivers. The interference can be reduced by appropriate resource allocation. In the latter case, radar sensing and communication functions are integrated in a single device. Nowadays, the design of beamforming and waveforms to improve spectrum utilization and communication performance is an important challenge for ISACs. Numerous researchers have investigated how to design ISAC waveforms [8, 57, 137] and beamforming [95, 131]. Due to the potential benefits of integrating sensing and communication functions, ISAC systems have attracted attention in several fields, such as in-vehicle networks, UAV communication and sensing [53].

Based on the fact that ISAC allows sensing and communication signals to share the same spectrum and waveform, ISAC can greatly reduce the delay of beamforming as well as beam alignment. Based on this, authors in [26, 54, 75, 103, 126] focus on intelligent transportation scenarios. The problem of predictive beamforming for connected vehicles is addressed in [54] and [126]. Unlike conventional beam tracking methods based on communication feedback, the approach based on ISAC technology does not require dedicated frequency guidance for the downlink and feedback for the uplink, which can eliminate the additional overhead generated by beam tracking and feedback, and improve the spectrum utilization and spectral efficiency of the system. Authors in [75] focus on the waveform design when communicating with connected vehicles. The joint waveform design problem is solved by ISAC operational frequency selection. A real-time traffic management system is presented in [103]. By using the ISAC approach, information-carrying terminals can quickly select the appropriate information uploading strategy to minimize transmission delay and improve user experience. An intelligent real-time dual-function radar system is presented in [26], based on ISAC technology that allows Automatic Vehicles (AVs) to perform both radar sensing and data communication functions, to maximize bandwidth utilization and improve communication security.

Different from cars, UAVs are widely used as transmission relays and for emergency communications because of their convenience and flexibility. Conventional UAVs are designed with separate sensing and communication modules, and each with separate spectrum and transceivers. ISAC technology allows sensing and communication modules to share the same hardware and spectrum, reduces the load on the UAV and improves the spectrum utilization [13]. Authors in [13, 110] investigate the application of ISAC in UAV networks. By using a unified spectrum and signal transceivers, the cooperative sensing capability of UAVs is greatly improved.

Although ISAC can greatly reduce the transmission delay, computing resources are different among IoT devices. Nodes with low computing resources to process computation tasks incur high latency, and those with high computing resources may cause resource wastage. The implementation of the metaverse requires not only fast data interaction between the virtual world and the real world, but also sufficient computing resources to ensure large-scale scene rendering in the metaverse. Therefore, how to reasonably utilize the computing resources among IoT devices is an issue that needs to be solved.

3.2 The Integration of Communication and Computing

The metaverse provides users with an immersive reality-expanding experience that requires not only the real-time interaction of large amounts of real data from the physical world, but also the rapid processing of data and the rendering of virtual scenes in real time. The metaverse contains numerous delay-sensitive and computation-sensitive application scenarios that current communication and computation technologies cannot support under resource-limited conditions [115]. The Integration of Communication and Computing (ICAC) can be understand from two aspects. On one hand, it uses computing technology to assist end-to-end communications to achieve low latency and high throughput. On the other hand, enhanced communication technologies can in turn enhance the allocation of computing resources. ICAC technology can not only effectively reduce network communication and computation delays, but also achieve reasonable resource allocation in the network [143].

ICAC can be divided into two paradigms: communication-centric [123] and computing-centric ones [140]. The former uses technologies such as fog computing and EC to optimize end-to-end communication by invoking ubiquitous computing resources in the network, thereby achieving low latency and high throughput. The latter collaborates the nodes in the network through communication technology, which can realize the reasonable scheduling of computing resources to improve resource utilization efficiency. Based on its advantages of low latency and high throughput, ICAC is widely used in highly dynamic scenarios such as IoV and UAV networks.

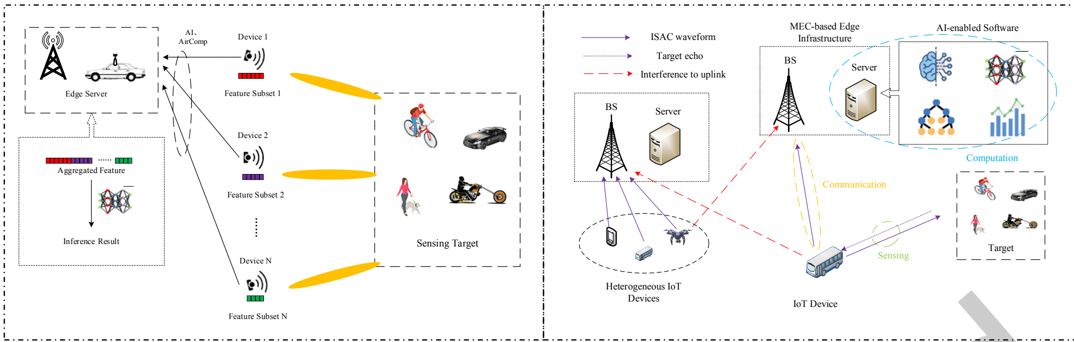
The implementation of various scenarios in the metaverse does not rely on a single network, but many heterogeneous networks collaborate with each other to provide intelligent services. Therefore, how to reasonably utilize the computing resources of heterogeneous networks and realize the collaboration among heterogeneous networks is a major problem. Current researchers have combined DT and ICAC, using ICAC to select suitable nodes for DT construction, and relying on powerful computing resources in DT to synthesize data in heterogeneous networks and make accurate decisions [30, 133].

Due to the massive access of users and intelligent terminals, network security and data privacy are also important issues in realizing the metaverse [106]. Currently, many scholars apply blockchain to guarantee user privacy and security. However, since transactions in the blockchain require consensus protocols to ensure data synchronization to achieve ledger consistency, it can cause serious resource consumption (such as computing and energy resources) and incalculable computing latency in the metaverse, where massive data support is required. Currently, based on ICAC, low-latency communication among nodes and rational utilization of computing resources can be achieved. Many researchers have started to focus on the use of off-chain computing resources [58] to improve resource utilization efficiency, and reduce energy consumption caused by large-scale on-chain computing.

3.3 The Integration of Sensing, Communication and Computing

The implementation and application of the metaverse has severe communication requirements in terms of extremely low latency, extremely high reliability, extremely large bandwidth and massive network access. The relevant applications in the metaverse should not only provide users with visual and auditory sensory experiences, but also with tactile, gustatory and even olfactory sensory experiences, which greatly increases the requirement for perceptual accuracy in the metaverse. The current limited wireless channels and computing resources can hardly satisfy the demand of applications in the metaverse. Due to the similarities of communication frequency bands, hardware devices, channel characteristics, and signal processing between communication and perception systems in the post-5G era, along with the current development of AI technology, the above conditions have greatly contributed to the development of SCC technology.

Generally, SCC technology can be regarded as a fusion of communication, sensing and computing technologies. Specifically, SCC applications can be classified as: communication-centric, perception-centric and computation-centric ones. Since SCC technology is currently in the exploratory stage, current research on SCC focuses on channel design (communication-centric) and multidimensional resources allocation (computation-centric). As shown in Fig. 4(a), the former focuses on obtaining a priori information about the channel by sensing techniques, and then using techniques such as AI and AirComp to achieve fast aggregation of channel state information, thus enabling efficient and green communication among users and between users and servers. As shown in Fig. 4(b), the latter focuses on the integrated allocation of multidimensional resources such as computation and communication. Based on ISAC technology, IoT devices can be equipped with radar sensing as well as communication capabilities. With radar sensing, the estimation of channel environment and terminal data can be realised. By selecting the appropriate uplink channel as well as the transmission frequency, the computational tasks can be reasonably offloaded to the servers with sufficient idle computational resources, so as to carry out reasonable allocation of computational and communication resources in the ubiquitous network. Based on SCC, it can not only relieve the challenge of limited channel resources arising from the access of massive terminal devices in the metaverse, but also carry out comprehensive scheduling of idle computing resources in the network, thus reducing the cost of metaverse realisation.



(a) Communication-centric SCC architecture **(b) Computation-centric SCC architecture**

Fig. 4. Technical details of SCC applications.

The realisation of the metaverse requires a huge number of intelligent terminals to access the network, and the contradiction between the current limited wireless resources and the huge number of users accessing the network is becoming intense. How to effectively utilise resources in ubiquitous networks is a topic of interest. As shown in Table 2, the authors in [29, 37] focus on this problem and propose SCC-based systems. The channel environment and computing resources of servers are detected by sensing techniques, and the allocation of communication and computation resources is dynamically adjusted according to the requirements of different intelligent applications for latency, energy consumption, model accuracy, and so on. Unlike [29, 37], the authors in [44, 93] focus on channel modelling under SCC. By applying AI and AirComp on the basis of ISAC, not only the dynamic modelling of communication channels can be achieved, but also spatial multi-functional computations can be performed simultaneously based on spatial degrees of freedom. Current research on SCC focuses on the modelling of communication channels and the effective utilization of multidimensional resources such as communication, computation and perception in the new paradigm. Research on how to use communication and computation technologies to improve perception technology is a direction to explore.

4 SCC SOLUTIONS FOR THE METAVERSE

As an immersive virtual world, the metaverse requires a large amount of real-time data to ensure the authenticity of user experience. There are various scenarios in the metaverse. However, different scenarios have different performance requirements for latency, data transmission rates, reliability, sensing accuracy, sensing ranges, computing resource utilization, etc. According to the size of network coverage, application scenarios in the metaverse can be mainly divided into the local space scene and the open space scene. The former refers to the scene with a small network coverage area achieved by using a few base stations. The latter refers to a scenario with a large network coverage area and multiple base stations. This section discusses existing technologies and solutions to meet performance requirements in different scenarios.

4.1 Solutions for Local Space Scenes

This subsection focuses on three scenarios: smart home, smart factory and medical health.

1) Smart Home: The majority of contemporary life is spent indoors, and with the explosion of COVID-19, people spend less and less time outdoors. Smart home is an embodiment of the IoT, which can identify activities of indoor individuals through ISAC, and obtain indoor information remotely through intelligent terminals, greatly improving the intelligence of people's life [38]. At present, people intend to experience the intelligence of life

Table 2. Comparisons of SCC related surveys.

Ref.	Focus	Description	Advantage	Disadvantage
[103]	ISAC	An ISAC-based real-time traffic management system	Focusing on dynamic network topologies	Efficient utilization of computing resources is not taken into account
[26]	ISAC	An ISAC-based intelligent real-time radar system	Concerned about the utilisation of radio spectrum resources	Ignoring the privacy and security of endpoint data
[30]	ICAC	An exercise autopilot scheme based on ICAC and DT	Taking the cost of autonomous driving services into consideration	Ignoring end-vehicle data privacy
[133]	ICAC	An edge resource management framework based on ICAC and DT	Concerned about the rational scheduling of heterogeneous resources at the network edge	Ignoring communication energy consumption
[37]	SCC	A DT-based SCC system	Concerned about system energy consumption and sensing beam gain	Ignoring communication reliability
[29]	SCC	A multi-unit collaboration-based ISAC approach for edge Intelligence	Focusing on multidimensional resource allocation and overall energy consumption	Ignoring dynamic scenarios and communication reliability
[93]	SCC	A wireless network framework integrating sensing, communication and computing	Considering the total sensor power constraint and energy consumption	Ignoring computation delays
[44]	SCC	An SCC-based MIMO transmission framework	Considering the limitations of wireless communication resources and supporting MIMO scenarios	Ignoring dynamic scenarios and reliability of communication links

brought by intelligent furniture, which is limited by the space dimension. The metaverse is a virtual world parallel to the physical world, where people can access in a digital body at any time and from anywhere through human-computer interaction devices. By arranging smart homes in the metaverse, the spatial limitations of smart homes in the physical world can be broken.

By arranging virtual scenes of each family in the metaverse, people can realize friends and family gatherings without leaving home, and provide a new paradigm for the current year-round workers and border guards to gather with their families. To achieve the above purpose, it requires not only access to large-scale smart terminals, but also accurate positioning and target recognition. In order to improve the experience of smart home users in the metaverse, the authors in [10, 18, 46, 77, 80, 118, 130] focus on target recognition in the smart home. To achieve high-accuracy target recognition, an algorithm for sleep monitoring is proposed in [130]. The model uses a statistical approach to detect the auto-correlation function of the channel state information as well as the indoor multi-path signals, which allows for faint signals in the room, to improve the accuracy of people's sleep monitoring. Different from the study in [130] utilizes traditional statistical methods to optimize target recognition accuracy and system latency, authors in [10] propose an ML-based target recognition system. It uses histogram equalization technique and FL to assist faster-R-CNN for subject behavior image recognition, which reduces the computational load. FL allows models to be transmitted with only model parameters and no sensitive data, which not only reduces the delay in data transmission, but also improves the accuracy of model detection.

Unlike [10, 130] where an existing action set is applied to train a target recognition model to improve target recognition accuracy, a transformer network consisting of a nearest-neighbour-based domain selector and a fine-to-coarse-grained cross-domain sensing framework is proposed in [80]. The framework embeds a hierarchical transformer structure based on convolutional maps and an improved linear layer into an end-to-end deep network to quickly identify meta-actions with a small number of action samples, which not only improves the accuracy of identification but also reduces the computational latency of target identification. The authors in [77] focus on the real-time nature of the sensory data, using Wi-Fi to transmit the sensory data to an edge server, where the data is fused and classified by a lightweight deep learning model. The system not only aims to accurately detect real-time activities of daily living, but also tries to improve the quality of data transmission. The authors in [46] have taken into account the memory constraints of AIoT devices and propose a lightweight CSI and a double hidden layer BP neural network based on particle swarm optimisation algorithm, by fusing the extracted relevant features to reduce the computational memory occupancy of the device and achieve real-time high-precision recognition.

Although the methods proposed by [10, 46, 77, 80, 118, 130] can effectively improve the accuracy of target recognition in smart home scenes, they do not effectively utilize multimodal data for a fine-grained perception of the environment to provide users with an immersive virtual experience. The authors in [18] propose a multimodal fusion-based activity recognition scheme for Wi-Fi platforms. The solution infers the potential behavioral information in the signal by introducing the Fresnel zone model to identify the Wi-Fi signal fluctuations caused by different human activities, and processes the acquired multimodal information using the multimodal decomposition bilinear pooling method and the AdaBoost algorithm, aiming to realize highly fine-grained activity identification. Smart home is realised in the metaverse, which needs the support of massive home sensors as well as smart terminals. The massive smart terminals can lead to a large amount of energy loss. The authors in [107, 128] focus on the energy consumption problem in smart home and use ML technology to achieve energy management in smart homes. The authors in [107] propose a deep reinforcement learning-based real-time energy management method to ensure real-time scheduling of end devices while minimising the energy consumption of the whole home. A reinforcement learning-based energy scheduling system for smart homes is proposed in [128], which employs a dual-delay deep deterministic policy gradient and data clustering-based algorithm to optimise energy scheduling for energy storage, heating and ventilation, and air-conditioning system in the smart home.

We summarize solutions for the application of smart home scenarios in Table 3.

2) Smart Factory: Along with Industry 4.0, manufacturing is gradually shifting towards intelligence and digitalisation. Digital connectivity between plant facilities and systems allows for deep analysis of plant-related matters. Different from the current digital exchange, the metaverse creates a virtual world made up of numbers, where the interaction between physical and digital space is achieved through digital technologies such as XR and DT, which can effectively improve the production efficiency of the factory.

Table 3. Summary of solutions for smart home

Ref.	Description	Optimization metrics: Identification accuracy	Communication delay	Energy consumption	Service response time	Communication reliability	System throughput	System costs	Positioning accuracy	User privacy and security
[130]	A statistical sleep monitoring model	√	√	×	×	×	×	√	×	×
[10]	An ML-based home monitoring system	√	√	×	×	√	×	×	×	√
[18]	A multimodal fusion based activity recognition scheme	√	×	√	×	×	×	×	×	√
[80]	A DL-based cross-domain perception framework	√	×	×	√	×	×	×	√	×
[107]	A DRL-based real-time energy management algorithm	×	×	√	√	×	×	√	×	×
[46]	A lightweight Wi-Fi-based target recognition strategy	√	√	√	√	×	×	×	×	×
[77]	A DL-based multi-activity recognition system	√	√	×	√	×	√	×	×	×
[128]	A RL-based smart home energy scheduling system	×	√	√	×	×	×	√	×	×

("√" if the protocol satisfies the property, "×" if not)

Smart factories usually involve tasks such as scheduling of network nodes as well as robots, and multi-machine clustering operations. There are large-scale machines in smart factories today, which generate massive amounts of data. In order to reallize smart factory in the metaverse, ultra-intensive data interactions place high demands on communication throughput and reliability for virtual-real interaction. To improve the communication throughput of smart factories, the authors in [34, 91, 111, 117] propose to build a framework for industrial IoT by ML and Software-Defined Networking (SDN). Placing the ML model at the network edge is helpful to reasonably match the terminal computational resources and the amount of computational tasks, which in turn improves the data transmission throughput in the case of limited communication bandwidth [111, 117]. Considering the real-time nature of task arrivals, an ML-based online task allocation framework has been proposed in [34], The framework considers the computational and communication latency constraints and exploits the structure of the original pair-wise problem formulation. The authors propose an online ML algorithm to obtain a feasible competitive ratio of task size and edge node data rate, thus providing a reasonable match between the amount of arriving tasks and the computational resources of the edge nodes to improve the system throughput. Considering the heterogeneity of smart factory networks, the authors in [91] propose an SDN-based IIoT network architecture. An ML-based bandwidth allocation method is proposed to ensure high-throughput data transmission in smart factories with limited bandwidth.

Unlike [34, 91, 111, 117] which focus on system throughput and latency, the authors in [92] propose a Smart Manufacturing Transfer Learning framework (FTL-CDP) for applications with limited training data. The FTL-CDP combines the concepts of federated learning and transfer learning to address the challenges of data scarcity and privacy for realising machine intelligence in Industry 4.0 environments. Distributed training is supported to protect data privacy while allowing trained models to be exchanged across different domains, such as target detection and pedestrian detection, to speed up the training process with a limited amount of data.

At present, multi-machine collaboration exists in the smart factory. For robots, production machines, goods, vehicles and other units, a unified platform is needed for scheduling. An edge-intelligent autonomous system for multi-user computation offloading in smart factories is proposed in [17], focusing on joint optimization of energy consumption and task latency. An improved deep deterministic policy gradient algorithm is proposed, which uses the actor network to formulate computation offloading policies, extending the operation space of each user device to be contiguous. That is to say, each task can be offloaded in any proportion, to improve resource utilization and open up possibilities for total system latency optimization.

However, applying smart factories in the metaverse requires massive computing resources to process the huge amount of data in the physical world to ensure the realism of the rendering of the virtual world and the accuracy of parameters in the factory. Currently, merely relying on EC cannot provide enough computing resources for timely data processing. Meanwhile, the data privacy cannot be guaranteed when the terminal data is directly uploaded to the virtual world. To overcome the shortage of computational resources, the authors in [4, 21, 59, 85] utilize DT to ensure the effective mapping of smart factories in the virtual world. By taking the advantage of DT time dimension, a DT-based dynamic interaction time scheduling scheme is proposed in [21]. A fast non-dominated sorting genetic algorithm is proposed to ensure that the system transmission delay and scheduling flexibility are optimised while energy consumption is minimized.

Unlike [21], the authors in [4, 59, 85] are more concerned about the privacy and security of the end data. Since constructing a DT model requires terminal nodes to frequently exchange data with the BS, by using FL to assist in constructing a DT model, the terminal nodes only need to upload their operational status to the DT [59, 85]. It not only reduces the communication pressure of the wireless network, but also ensures the privacy and security of terminal data. A blockchain-assisted hierarchical federated learning platform to support Industry 4.0 is presented in [4]. The platform integrates DT into CPS to accurately capture the characteristics of IIoT devices. It also employs a two-stage FL algorithm to further release the communication pressure, and uses blockchain to protect the global model. DT-based resource scheduling for smart factories has been implemented in real-world factories. For example, Nvidia Omniverse allowed BMW to combine its physical-world factories with DT, AI, and robotics, to improve the precision and flexibility of factories, increasing BMW's planning efficiency by 30% [115].

We summarize solutions for the application of smart factory scenarios in Table 4.

3) Medical Health: Since large-scale IoT devices are used in the healthcare, Healthcare Internet of Things (HIoV) emerges. The application of some revolutionary technologies, such as VR, big data, DT and blockchain, can greatly reduce the cost, enhance the performance and expand the coverage of healthcare services [31]. The metaverse allows 2D virtual images to be transformed into 3D virtual scenes, allowing users to immerse themselves in healthcare services. By placing intelligent medical scenarios in the metaverse, HIoV can not only make quick judgments based on the fusion of virtual and real-world information to assist medical workers, but also enable doctors from different hospitals to share a room for medical treatment and remote consultations in emergency situations.

In order to accurately identify the resulting disease based on the patient's demeanour, smart healthcare requires a high degree of accuracy in target recognition. The authors in [1, 9, 19, 42] are concerned with the problem of

Table 4. Summary of solutions for smart factory

Ref.	Description	Optimization metrics								
		Identification accuracy	**Communications delay**	**Energy consumption**	**Service response time**	**Communications reliability**	**Communications throughput**	**System costs**	**Terminal connection density**	**Endpoint Privacy and Security**
[117]	A DL-based industrial IoT architecture	×	×	√	×	√	√	×	×	×
[91]	A SDN-based heterogeneous industrial Internet architecture	×	√	×	√	√	√	×	×	×
[85]	A DT-based industrial IoT framework	√	√	√	×	√	×	×	×	×
[59]	A DT industrial IoT edge network	×	√	×	√	×	×	√	×	√
[17]	An autonomous system for multi-user computation offloading	×	√	√	√	×	×	×	√	×
[21]	A DT-based scheduling system for job shops in smart factory	×	√	√	√	√	×	×	×	×
[34]	An ML-based online task assignment framework	×	√	×	√	×	√	×	×	√
[92]	A cross-domain predictive federated transfer learning framework	×	×	×	√	×	√	×	√	√
[4]	A blockchain-based platform for hierarchical federated learning	√	×	√	×	√	×	√	×	×
[111]	A data transfer architecture based on cloud edge collaboration	√	×	√	×	√	×	√	×	×

(“√” if the protocol satisfies the property, “×” if not)

disease recognition accuracy, in which the authors in [1] propose a DL-based system for automatic detection of non-invasive patient discomfort. Data mining association rules are utilized to transform these detected key points into six main body organs, and distance and time thresholds are applied to classify movements as associated with normal or discomfort conditions. An RL-based method for intelligent selection of EEG signals is proposed in [42]. The method selects a subset of features by introducing the calculation of entropy and Pearson’s correlation coefficient, and achieves intelligent selection of multi-domain EEG signal features through the interaction between the subject and the environment. The authors in [9, 19] propose to build a disease recognition system based on

DT, which builds and trains multiple models of surveillance data in real-time healthcare facilities, to improve the accuracy of disease recognition through multimodal data fusion.

A DT-based telemedicine simulation system is proposed in [87] to enable an immersive user experience. The system is divided into three layers: the perception layer, the network layer and the application layer. The perception layer uses perception technology to obtain real-time data about the environment and patients in the operating theatre. The network layer uses DL-based interpolation methods and an improved AG-GAN algorithm to filter and denoise the data from the perception layer and historical patient information, to generate accurate patient information models in the DT. The application layer generates patient information models based on head-mounted devices by XR and AR technologies, to improve accuracy and immersion during remote surgery execution. Authors in [71] design an MEC-based health monitoring system, which focuses on the joint optimization of system resource utilization ratios and costs. The system is divided into two sub-networks: Wireless Body Area Networks (WBANs) and beyond-WBANs. Two algorithms, cooperative game and decentralized non-cooperative game, are developed to solve the channel resource allocation problem for WBANs and to minimize the system cost of the healthcare IoT, respectively.

The privacy and security of healthcare applications is challenging to ensure, because they require access to a large amount of patient information to ensure the accuracy of disease diagnosis, but the patient's information contains a large amount of private information. Authors in [39, 40, 83, 84] focus on privacy protection in intelligent healthcare systems. Authors in [40, 83] propose two smart healthcare systems based on blockchain and EC technologies. Using EC allows end-user data to be calculated at the network edge, reducing the computational pressure on the cloud. Blockchain technology and smart contracts not only enable efficient interaction between patients and medical procedures, but also ensure secure data delivery. An FL-based Alzheimer's disease detection system is presented in [39] to ensure the integrity of the original data, and protect the confidentiality of the classification models. In addition, a new asynchronous privacy-preserving aggregation framework is designed to protect the model aggregation process between the client and the cloud.

Authors in [84] are concerned with privacy and security while at the same time focusing on the communication efficiency of the system. A DT enabled asynchronous learning is proposed for classification tasks in eHealthcare systems. The learning system is developed to improve the communication efficiency in eHealthcare systems by sending only the extracted features during the learning process instead of sending the entire learning model. This allows resource-constrained IoT devices to participate in the global model generation.

We summarize solutions for the application of medical health in Table 5.

Lesson 1: Clearly, the application of local spatial scenarios in the metaverse places high demands on target recognition accuracy, data privacy and security. The problem of target recognition accuracy is addressed mainly by a combination of perception and computation. DL can be iterated step by step using simple models, so that the perceptual information acquired by the device can be processed at a fine granularity. FL allows the information acquired by the perceptual device to be trained locally without the need of uploading the private data to the cloud, ensuring data security.

Nevertheless, current information has a variety of types and forms, and the combined perception and computing method cannot obtain multidimensional information to ensure high recognition accuracy. At present, communication and perception technology tends to be the same in terms of both hardware and spectral characteristics. On one hand, using communication-perception integrated signals can achieve multi-dimensional perception. On the other hand, it can achieve the acquisition of the best transmission channel to ensure reliability and throughput of tranmismitted data. Therefore, it is promising to utilize SCC technology to realize the multimodal data transmission and processing to support the application requirements of local spatial scenes in the metaverse.

Table 5. Summary of solutions for healthcare

Ref.	**Description**	**Optimization metrics**							
		Identification accuracy	**Communication delay**	**Energy consumption**	**Service response time**	**Communication reliability**	**Communication throughput**	**System costs**	**Users Privacy and Security**
[1]	A DL-based non-invasive automated patient discomfort monitoring system	√	√	×	×	√	×	×	√
[19]	A DL-based context-aware healthcare system	√	√	×	×	×	×	×	√
[87]	A DT-based telemedicine simulation system	√	√	×	√	×	×	×	×
[71]	An MEC-based health monitoring system	×	√	√	√	×	×	√	×
[40]	A home healthcare framework	×	√	×	×	×	√	×	√
[39]	A privacy-preserving Alzheimer's detection system for healthcare	√	√	×	×	×	×	√	√
[83]	A blockchain-based patient-centric HIoV system	×	√	×	√	×	√	×	√
[42]	An RL-based multi-domain EEG signal selection system	√	×	×	√	×	√	×	×
[9]	A DT-based healthcare control system	√	√	×	√	√	×	×	×
[84]	A DT-ASFL based healthcare task classification system	×	√	×	√	×	×	√	√

("√" if the protocol satisfies the property, "×" if not)

4.2 Solutions for Open Space Scenes

The metaverse's application scenarios include not only indoor scenarios such as smart homes, smart factories, and smart healthcare, but also open space scenarios such as ITS, SAGIN, and UAV networks. Open space scenarios have higher requirements for latency, connection density, and network coverage compared with indoor scenarios. The limited wireless communication and computing resources of traditional network infrastructures can not always satisfy the demands of the above application scenarios. The metaverse is a virtual world that integrates many technologies such as AI, DT and EI to make optimal decisions for the allocation of network resources. The ultimate goal of the metaverse is to turn the physical world into a subset, and all corners of the physical world need to be present in the metaverse, but terrestrial cellular networks cannot meet this need of "anywhere" coverage. At present, smart cars, UAVs, and satellites can provide computing support for the realisation of the metaverse, and act as sensor perceptors of environmental information around the metaverse to realise the desire for full coverage. The following content specifically summarises the relationship of IoV, UAV networks and SAGIN with the metaverse as well as current research on these three scenarios.

1) Intelligent Transportation: It is a complex scenario consisting of systems such as vehicle control, traffic monitoring and travel information [144]. Information about road traffic can be obtained through IoT sensors, edge infrastructure, different types of surveillance cameras and other information sources, and various applications in smart transportation are realized based on the processing of heterogeneous information. As a virtual world created by AI, the metaverse processes the data perceived by the physical world in real time to provide users with an immersive metaverse experience. Currently, edge computing and cloud computing can provide computing resources for metaverse. However, the expensive construction cost of the edge base station as well as the operational expenses become the bottleneck for the implementation of metaverse. With the development of IoV, on the one hand, vehicles are equipped with powerful computing resources to provide users with a smart driving experience; on the other hand, vehicles with computing resources are able to push the communication and computation power to the network edge [12]. Wireless communication technology and IoV system architecture allows idle vehicles to be used as small edge base stations. By comprehensively utilising these idle computing resources, computing tasks can be processed in real time.

ITS is a real-time and complex system, the network topology is always changing. In this highly dynamic scenario, the requirements for both sensing and communication capabilities are extremely high, requiring low latency, large system throughput, high reliability, great resource utilization efficiency, real-time and accurate detection of vehicle locations [64]. How to ensure the rational usage of heterogeneous resources as well as to ensure the reliable and stable communication among intelligent terminals is a problem worth discussing. Through advanced technologies such as AI, DT, EC and SCC, intelligent transportation scenarios can be mapped from the physical world to the virtual world in the metaverse. Based on multidimensional ground sensing information and powerful computing resources in the metaverse, latency-sensitive applications can be implemented, and global decisions can also be made quickly and accurately, providing users with smart transportation services [33].

To ensure the user's traffic experience, authors in [67] propose an RL-based generative adversarial network for joint optimization of transmitted packet rates, power consumption, and throughput. In addition, the authors in [30] use virtual world resources to optimize throughput in vehicular networks. Two mechanisms are proposed: cooperative drive based on auction game and distributed drive based on coalition game. The former is used to quickly determine the heads and tails of vehicle rows, and the latter is used to determine the optimal group distribution to minimize the data transmission delay and drive costs among DTs.

Since intelligent transportation is realized in a dynamic environment, the intermittency and unreliability of communication among vehicles greatly degrades the performance of intelligent transportation. To ensure the reliability of virtual and real data communication, the authors in [62] focus on communication throughput along with communication reliability. An algorithm based on EI is proposed to jointly optimize transmission delay, offloading energy consumption and packet loss rates. In addition, the work in [58] pays attention to the security while focusing on the reliability of Telematics communication. To cope with the heterogeneous nature of dynamic IoV, a blockchain-assisted asynchronous federated learning architecture is proposed, which performs asynchronous learning by optimizing the selection of participating nodes and dividing aggregation slots into local and global ones. In addition, a DAG-based hybrid blockchain is designed to store and validate learning parameters of the model to ensure the reliability of model learning and shared data.

Authors in [139] are concerned about the connectivity of mobile users in heterogeneous networks to improve the user's experience. A data synchronisation framework based on DT is proposed to realize distributed data

Table 6. Summary of solutions for IoV

Ref.	Description	Optimization metrics							
		Positioning accuracy	Communication delay	Energy consumption	Service response time	Communication reliability	Communication throughput	Resource utilisation	Users Privacy and Security
[67]	An RL-based generative adversarial network	×	√	×	×	√	√	√	×
[30]	A DT-based co-driving solution	√	√	√	×	×	√	×	×
[136]	An EI-based framework for real-time edge caching and computation	×	√	√	×	√	×	√	√
[133]	An IoV edge computing network based on DT and multi-intelligent learning	×	√	√	√	×	×	√	×
[74]	An EI-based IoV framework	×	√	√	√	×	√	√	×
[62]	An EI-based offloading and migration algorithm in the IoV	×	√	√	×	√	×	×	×
[58]	An IoV architecture based on FL and blockchain	×	√	×	×	√	×	×	√
[16]	An MEC-based framework for adaptive bitrate-based multimedia streaming	×	√	×	√	√	√	×	×
[139]	A DT-based data flow prediction model for heterogeneous vehicular networks	√	√	×	×	√	×	×	×

("√" if the protocol satisfies the property, "×" if not)

synchronisation. An MEC-based framework for multimedia streaming is proposed in [16]. An adaptive quality-based block selection algorithm is designed by combining heterogeneous edge caching and communication resource constraints, which determines the bandwidth allocation based on a beneficiary function. The framework aims to achieve joint optimisation of media stream transmission throughput, transmission rate and transmission reliability.

The application of intelligent transportation in the metaverse requires a large amount of communication and computing resources. How to realize the application of intelligent transportation in the metaverse under conditions of limited resources is a hot research topic. An EC-based framework for real-time IoV edge caching and computing management is proposed in [136], which tries to solve the joint optimization problem of service caching, request scheduling and resource allocation by using Lyapunov optimization, matching theory and coherent alternating direction multiplier methods in an online and distributed manner. In addition, the authors in [133] focus on different types of intelligent vehicles with different capacities, different applications with different resource requirements, and unpredictable vehicle topologies. The article combines DT with EI to adaptively adjust the potential cooperation among different vehicles to form multi-agent learning groups, effectively improving the utilization of edge resources. Different from studies in [133, 136] using big data samples for training models to achieve resource allocation, authors in [74] propose an EI-based IoV framework to address the high dynamics of computing task arrival, where imitation learning-based Branch-and-Bound (B&B) algorithms are utilized to achieve excellent learning performance with a small number of training samples.

We summarize solutions for the application of IoV in Table 6.

2) UAV Network: Compared to conventional aircraft, UAVs are small in size, and their mobility and flexibility have been greatly enhanced [76]. Mapping UAV networks from the physical world to the virtual world, based on the computing resources of the virtual world, allows the application of UAV networks be enhanced with the minimum cost. In the context of metaverse, the SCC-based technology can acquire the changes of wireless communication and physical environment in real time, which can provide a strong support for the information interaction among UAVs and their trajectory optimisation [41]. Based on the mobility of UAVs, UAV networks can provide temporary resource support scenarios with temporary surges in computing and communication needs, which can improve the user experience in the metaverse. Currently, due to the limitation of UAV sizes, computing resources and energy it can carry are limited, and thus how to maximise the use of UAV's limited resources to provide persistent and reliable response mapping for virtual worlds is an important issue.

In order to improve the rational utilization of limited UAV resources, the authors of [73, 109, 135, 141] jointly optimise UAV trajectory, wireless resource allocation and computing task offloading. The authors in [135] propose a DRL-based algorithm to select movement trajectories for UAVs, thus ensuring that UAVs utilise limited resources to serve users. To minimise energy consumption of UAVs, an EI-based offloading method of UAVs to communities is proposed in [73]. The UAV service community and computational resource allocation are selected through a joint trajectory design and task scheduling algorithm. Different from [73, 135], the authors in [141] are concerned with the reliability of data transmission with limited resources. By jointly considering the control of UAV manoeuvrability and transmission power as well as the scheduling of air-to-ground data transmission, a bipolar optimisation problem is formulated, and an iterative optimisation algorithm based on the direct multiple-shot method and the successive quadratic programming technique is proposed to solve the above problem. Authors in [109] are concerned not only with UAV energy consumption and transmission reliability, but also with UAV data transmission throughput. By jointly optimising the flight trajectory and power allocation of the human-machine, the lower bound of the UAV transmission throughput is improved while UAV manoeuvrability and communication covertness can be guaranteed.

In order to ensure the privacy and security of user data during transmission and prevent eavesdroppers, the authors in [27] consider the availability of perfect Channel State Information (CSI), and propose two different optimisation algorithms. For the scenario where the user link and potential target location are ideal, a penalty-based algorithm is used to obtain a high-quality solution and the phase shift of the IRS is solved by an optimisation method. A robust algorithm based on the symbolic deterministic approach is proposed for the practical scenario where the CSI is imperfect and the potential target location is uncertain.

Due to their mobility and flexibility properties, UAVs are widely used for communication after disasters and in harsh environmental conditions [2, 7, 50, 129]. An RL-based emergency communication system is proposed in [50], which aims to ensure the maximum UAV coverage by optimizing UAV energy consumption and UAV path selection. Authors in [2] not only optimize the communication coverage, but also try to improve resource utilization efficiency. The classical B&B algorithm based on relaxation induced neighborhood search is leveraged to jointly optimize the UAV base station distribution and the user assignment to ensure the maximum number of user connections with a limited number of UAVs. In addition, a DL-based dynamic UAV-to-UAV communication

Table 7. Summary of solutions for UAV network

Ref.	**Description**	**Optimization metrics**							
		Scope of Coverage	**Communication delay**	**Energy consumption**	**Service response time**	**Communication reliability**	**Communication throughput**	**Resource utilisation**	**Position accuracy**
[135]	A UAV-to-everything heterogeneous data communication framework	√	×	×	×	√	√	√	√
[50]	A DT-based ramp merging system	√	√	√	×	×	×	√	√
[2]	Multi-standard UAV base station placement for disaster management	√	√	×	√	×	×	√	×
[7]	A framework for DL-based dynamic UAV-to-UAV communication models	√	√	×	√	√	×	×	×
[129]	A 3D deployment system for multiple UAV-mounted base stations	√	√	×	√	√	×	√	√
[141]	A joint optimisation framework for UAV mobility control and data transmission scheduling	×	×	√	√	×	×	×	×
[109]	A UAV covert communication system for maximising minimum throughput	×	×	√	×	√	√	×	×

("√" if the protocol satisfies the property, "×" if not)

model is proposed in [7] to provide firefighters with a high-quality and wide-range fire video. The location of the UAV, video resolution and transmission are jointly optimized based on a DL approach to improve the long-term quality of experience. Authors in [129] propose a 3D deployment system with multiple UAV-mounted base stations, aiming to maximize the UAV service coverage.

We summarize solutions for the application of UAV networks in Table 7.

3) SAGIN: The goal of the metaverse is to build a virtual world that encompasses the physical world; in short, entities in the physical world are presented in the virtual world of the metaverse, which requires a vast

Table 8. Summary of solutions for SAGINs.

Ref.	Description	Optimization metrics							
		Communication delay	**Energy consumption**	**Service response time**	**System resource utilisation**	**Transmission throughput**	**Scope of coverage**	**System capacity**	**Endpoint data privacy**
[65]	An EC-based SAGIN resource scheduling framework	√	×	√	√	×	×	×	×
[134]	A method based on DRL and virtual network architecture	√	×	√	√	×	√	×	×
[104]	A SAG-IoRT framework	×	√	×	√	√	×	√	×
[88]	A blockchain-based framework for secure federated learning	√	×	√	×	×	×	×	√
[24]	A reconfigurable SAGIN architecture based on SDN and NFV	×	×	√	√	×	√	×	×
[90]	A task offloading decision for SAGINs	√	√	×	√	×	×	×	×
[25]	An optimisation framework for task scheduling and power control in SAGINs	√	√	×	√	√	×	×	×
[20]	A topology-aware joint learning framework for SAGINs	√	×	√	√	×	×	×	√

("√" if the protocol satisfies the property, "×" if not)

number of end devices in the physical world to access the network. It is expected that by 2030, more than 500 billion IoT devices with sensing, computing and communication capabilities will be connected to the network, and there will be a surge in the amount of data and information exchanged among different IoT devices [5]. Currently, terrestrial network segments are unable to provide stable network access to users in remote areas as well as non-terrestrial areas due to limitations in coverage and communication capacity [88]. As a comprehensive network, it mainly consists of an air-based network, a space-based network and a ground-based network [81]. Combining the strengths of all three, SAGIN significantly improves network coverage, capacity and flexibility. It can provide a broad coverage for the realisation of the metaverse by rationally allocating computing and communication resources according to different applications of the metaverse.

SAGIN offers a higher quality of seamless connectivity than traditional communication networks. Due to the heterogeneous, time-varying and self-organizing nature of SAGINs, their deployment face huge challenges in terms of heterogeneous and limited network resources, and large communication delay. Thus, resource allocation of SAGINs is extensively studied by the authors in [24, 65, 104, 134]. An EC-based framework for SAGINs is presented in [65], which aims to minimise the computational latency among IoT devices through the joint scheduling of computational tasks, bandwidths and drone locations. A DRL-based resource scheduling approach for SAGINs is presented in [134]. The authors model heterogeneous resource scheduling as a virtual network embedding problem and solve it by a DRL-based cross-domain algorithm. Concerned about the coordination of heterogeneous resources in dynamic networks, the authors in [24] propose a reconfigurable SAGIN architecture based on software-defined networking and virtualisation of network functions. The architecture introduces virtual link rate adaptation among virtual network functions to improve the utilisation of network resources. Unlike [24, 65, 134], which focus only on the optimisation of resource utilisation and latency, the authors in [104] also focus on the energy consumption of UAV-assisted SAGINs. Joint optimisation of device connection scheduling, power control and UAV trajectory selection is performed, and a three-block resource allocation method is proposed, which employs variable substitution and successive convex approximation for real-time resource allocation to maximise resource utilisation while minimising energy consumption of UAVs.

Due to the limited computational resources of UAVs and satellites, an effective offloading decision and computational resource allocation scheme is crucial. The authors in [90] study the problem of resource offloading and computational resource allocation in SAGINs. Joint optimisation of wireless device latency, UAV energy consumption and computational task offloading is performed, and a minimisation method based on block-continuous upper bounds is proposed. An optimisation framework for task scheduling and power control is presented in [25]. The framework jointly optimises task scheduling and power control while considering intermittent time windows, and proposes an approximation algorithm, i.e., a balanced energy and maximisation algorithm.

Because of the heterogeneous of SAGINs, the large network space, and the big number of end-users accessing the network, how to guarantee the privacy and security of users in the SAGIN is also an issue of concern. Based on the advantage that FL enables end nodes to complete the global model without uploading the original private data, the authors in [20, 88] propose to secure the end data of the SGAIN based on FL. Authors in [88] combine blockchain and FL to propose a joint asynchronous dominant participant selection algorithm to implement traffic offloading in the SAGIN. Authors in [20] propose a FL-based topology-aware algorithm to secure end-user data by enabling the aggregation of multi-level models.

We summarize the solutions for the application of SAGINs in the metaverse in Table 8.

Lesson 2: It is clear that open space scenarios in the metaverse are highly dynamic, which place high demands on latency and reliability. Joint communication and computing resource scheduling is currently used to reduce data transmission latency and improve transmission reliability, based on techniques such as EC and ML. The network diversity can lead to heterogeneous types of user requirements. Current sensed data information combined with historical can be utilized to support DT to make optimal decisions for resource scheduling.

Nevertheless, the implementation of the metaverse requires the real-time interaction of massive data generated in both virtual and real worlds, and the limited computing resources of terminals and spectrum resources in the network make it difficult to cope with latency sensitive requirements in highly dynamic scenarios. The development of SCC technologies can make full use of the limited spectrum resources, enable fast beam alignment, efficiently integrate computing and storage resources of base stations and terminal devices, and enable efficient collaboration among smart devices.

5 RESEARCH CHALLENGES AND OPEN ISSUES

In the previous section, we discuss and summarize the research based on SCC technologies to solve related problems in the metaverse. However, there are still some research challenges and open issues including data mapping, interaction between the physical world and the virtual world, data synchronization and multimodal data fusion, which are discussed as follows.

5.1 SCC-based Data Mapping

The realization of the metaverse requires the support of a large amount of data information in reality, and the current limited wireless channel resources limit the realization of the metaverse. In order to break through the limitation of channel resources, Multiple-Input Multiple-Output (MIMO) technology is mainly used to improve bandwidth resources and channel utilization. However, traditional MIMO technology mainly focuses on insufficient load, and cannot cope with the current situation that the number of IoV terminals is much larger than that of base stations. Therefore, seeking a technology that can achieve high-reliability, low-latency data mapping from the physical world to the virtual world is a direction worth researching.

At present, some scholars use NOMA technology to assist the implementation of MIMO. Although MIMO-NOMA technology can help terminals transmit data through power domain multiplexing, the design of its beamformers requires accurate channel state information. However, accurate channel status information is not easy to obtain, and the current algorithms used for NOMA produce unacceptable signaling overhead and high computational complexity in the face of large-scale user connections, which cannot meet the requirements of ultra-low latency in the metaverse. Based on the collaboration of communication, perception and computing technology, SCC can leverage computing resources of the ubiquitous network to quickly analyze the perceived environment and channel information when performing virtual-real mapping. Nevertheless, SCC puts the communication signal and the perception signal in the same transmission channel, which causes interference when transmitted at the same time. The current multi-access technology cannot avoid the unacceptable signal error caused by concurrent users, so developing an effective multiple-access technology for SCC is also a topic worth studying.

5.2 SCC-based Interaction Between The Physical World and The Virtual World

At present, the metaverse is still in a state of “cute new”. Besides technical limitations, the entrance problem of meta-universe applications also needs to be solved urgently. Current VR technology can realize the interaction between the physical world and the virtual world. However, the current VR device mainly presents the acquired video stream in the user’s field of vision, and the obtained application scenarios are fixed and cannot change with the real world scene. The current terahertz communication technology can achieve large-bandwidth and low-latency data transmission, but its reliability needs to be improved. Therefore, designing a reliable virtual and real data interaction with ultra-low latency to solve the metaverse entrance problem is necessary.

The purpose of the metaverse is to provide users with a realistic virtual world and an immersive experience. A realistic virtual world requires not only visual and auditory information, but also other perceptual information such as touch, smell, and taste to improve the user’s real experience. The current VR/AR technology can only provide auditory and visual information in the virtual world, and the acquisition of other sensory information such as touch is still an open issue. The current brain network technology can realize the access to many sensory information of the user by acquiring the relevant neural information of the user’s brain, but the different sensory information makes the feature dimension increase abruptly, and the reliability of information interaction and the classification of different sensory information need to be tackled. Although some solutions have been proposed to realize interactive information interference detection [112], accurate information classification [125] and reduction of information feature dimensionality [114]. Facing a large number of users in the metaverse, multisensory information acquisition still has challenges in practice: 1) The acquisition and processing of multi-sensory information and the rendering of virtual world scenes have a huge demand on computing resources; 2) The increase in computing resource demands is accompanied by a sharp increase in energy consumption; and 3) High energy consumption eventually leads to increasing resource costs for users to enter the metaverse.

5.3 Data Synchronization in The Metaverse

The metaverse is a virtual world consisting of a mapping of objects in the physical world. There are various types of service providers in the metaverse, and each may require additional information to enhance its virtual services. For example, a virtual tour provider intends to offer the user with the nearest live concert or some event information while conducting a tour. The use of traditional fixed and static sensors to collect data of the physical world can meet the requirements, but the location of surrounding activities cannot be static, and different activities require different perception accuracy. Deploying static sensors is expensive, and can be challenging in rural and mountainous areas. Thus, how to dynamically obtain data from the physical world and achieve ultra-low latency data mapping to ensure near real-time virtual and real data synchronization needs to be considered.

Given the flexibility of drones and autonomous vehicles, many researchers leverage a set of mobile IoT devices to address the aforementioned static sensor deployments [61]. Although mobile IoT devices can dynamically obtain data from the physical environment, in the face of massive data processing and transmission, computing resources of these devices are not enough to support the metaverse's requirements for real-time virtual-real data synchronization. To solve the above problems, the use of SCC technology can realize the multi-agent collaboration between mobile IoT devices and nearby base stations, to ensure the dynamic acquisition and timely processing of environmental data. However, these agents are vulnerable to malicious attacks, and how to ensure data security is challenging to deal with.

5.4 SCC-Enabled Multimodal Data Fusion

As a virtual world created by the digital avatar of physical world affairs, the metaverse needs to obtain massive real-world data to maintain the operation of the metaverse. The metaverse intends to provide users with a highly immersive experience, so it needs to acquire and process data from various modalities in the real world. Multimodal data can view things from different angles and dimensions, achieve fine-grained analysis, and restore real-world affairs in the virtual world. However, since data from different modes may represent the same information, information redundancy inevitably occurs when multimodal data fusion is conducted. In the scenario of the metaverse, information redundancy not only generates a huge waste of resources, but also greatly aggravates the congestion of wireless networks. Consequently, how to effectively integrate multimodal data in the metaverse is a direction worth studying.

At present, most multimodal data fusion algorithms use the human way of thinking to abstract the semantics of different modal information by matrix decomposition and linear combination. Nevertheless, this method not only generates unnecessary energy consumption, but also cannot meet the delay requirements of applications in highly dynamic environments. SCC technology can maximize the utilization efficiency of limited computing resources and ensure the speed and accuracy of data fusion. However, SCC technology requires novel channel models to meet the transmission reliability requirements of communication and sensing integrated signals. In addition, the implementation of SCC technology demands for strict hardware conditions, which greatly increases the realization difficulty of metaverse applications.

5.5 AI-Based Heterogeneous Resource Allocation for Metaverse

The realisation of metaverse not only relies on the terrestrial base station network, but also requires the support of multiple network resources such as UAV network, SAGIN network and IoV. The use of multiple heterogeneous network resources can effectively alleviate the pressure of resource shortage caused by ultra-large-scale user access. However, different network architectures have different requirements for data transmission rates, reliability, and delay, and thus how to ensure the effective usage of heterogeneous network resources is an interesting topic.

Current research uses NFV to unify the scheduling of resources, which can reasonably allocate relevant resources according to different applications and ensure the QoS. However, the current NFV is the interface of each major service provider, and it is impossible to achieve a unified interface among different service providers. AI, as a technology that simulates intelligent thinking of human beings, can make reasonable decisions by comprehensively utilising the relevant data. By placing AI algorithms at the network edge and in the cloud, it is possible to reasonably allocate relevant resources for each application based on the acquired data. Although AI algorithms can make reasonable decisions, the application of AI also brings new security issues. For example, the reliability of models trained by AI algorithms, and whether the data of learning models are safe and reliable. Therefore, at present, how to ensure the reliability and trustworthiness of AI is also an issue worth considering.

5.6 AI-Enabled Privacy and Security Issues of Metaverse

The realisation of metaverse enables users to experience the joys of outdoor living without having to leave their houses. People participate in metaverse life in the form of digital avatars through smart terminal devices, enabling an immersive experience of activities such as shopping, partying and working. While real-time immersive experiences in the metaverse provide users with perfect sensory pleasure of the virtual world, they also bring corresponding challenges: 1) The secure integration of sensitive data when users in the physical world interact with their digital avatars in the virtual world; 2) The boundaries between virtual and real worlds become increasingly blurred as the metaverse evolves, which makes the metaverse hyperspatial and this greatly increases the meta complexity of trust management in meta-universes; 3) Users can freely access different meta-universes simultaneously in different scenarios and interaction modes, which also poses a challenge to ensure rapid service authorisation, compliance auditing, and accountability enforcement for seamless service mitigation and multi-source data fusion.

At present, based on the characteristics of invariance, decentralisation and interoperability, blockchain can provide a trustworthy interaction environment for the realisation of the metaverse. Based on the irreversible characteristics of blockchain, it can effectively prevent malicious users from tampering with their behavioural information and conceal their malicious behaviour in the virtual world. However, the realisation of the metaverse requires the support of real-time massive data, and it is impossible to process such a huge amount of data in real time only based on the blockchain. AI with blockchain can intelligently select safe and reasonable offloading objects for computing tasks, to improve the efficiency and throughput of blockchain, and provide a safer virtual experience for metaverse users. However, when the AI model is being trained, it needs to obtain the information of various intelligent terminals, and how to distinguish the malicious information to ensure the reliability of the AI training model is also an issue to be considered.

6 CONCLUSIONS

In this article, we first introduce the architecture, current development and related characteristics of the metaverse. Then, the enabling technologies that underpin the implementation of the metaverse, such as 6G networks, DT, EI and blockchain, are introduced. Focusing on enabling technologies, we point out the important role of SCC for the development of the metaverse. After that, we discuss solutions or metaverse scenarios such as smart home, smart factory, smart medical, smart transportation, UAV network and SAGIN in terms of recognition accuracy, communication throughput, communication latency, user data privacy and communication reliability. Finally, we point out some research challenges and future research directions of SCC for the metaverse.

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