The Microverse

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Contributor: Qian Qu, Mohsen Hatami, Ronghua Xu, Deeraj Nagothu, Yu Chen, Xiaohua Li, Erik Blasch, Erika Ardiles-Cruz, Genshe Chen

The proliferation of Internet of Things (IoT) technology combined with evolving artificial intelligence (AI) and machine learning (ML) promote unprecedented advancements in ubiquitous and seamless services for human activities. In the context of smart cities, the fusion of the metaverse with the IoT—an expansive network of interlinked devices and sensors—heralds a transformative era in urban interaction, blending the digital with the physical.

Keywords: metaverse ; digital twins (DT) ; blockchain ; Internet of Things (IoT) ; smart public safety surveillance (SPSS)

1. Introduction

The proliferation of Internet of Things (IoT) technology combined with evolving artificial intelligence (AI) and machine learning (ML) promote unprecedented advancements in ubiquitous and seamless services for human activities [1]. The technical evolution in internet technology has made smart cities a reality for the foreseeable future. Over the past decade, since the concept of "smart cities" was officially defined by the National Institute of Standards and Technology (NIST) in 2014, more than 200 smart city projects have been launched [2]. Many experiences and lessons were learned, preparing society for a more intelligent, efficient, and sustainable future [3].

Many open questions are yet to be addressed in designing, creating, managing, and living in a smart city. One of the top challenges is the *scalability* of today's smart city solutions to many sensors. Not only does the amount of data being generated continuously and drastically grow, but the complexities also increase significantly as more intelligent functions are added. For example, IoT network infrastructures are often under different administrations when initially built, but more novel applications or services require resources across domain boundaries. Network slicing (NS) technology has been identified as an acceptable approach to address cross-domain services [4][5]. NS allows users to create logical networks for individual applications using network devices belonging to different domains. However, creating and managing a network slice that involves sensing, computing, communicating, and data-storing devices deployed across domains is nontrivial. There is a compelling need for a holistic solution that enables full-spectrum smart city operation monitoring, analyzing, decision-making, and the taking of actions dynamically in real-time.

The metaverse has recently attracted interest from academia and industry [6]. Many expect the metaverse to redefine how people live, work, and socialize by enabling a seamless interweaving of the physical world with a virtual cyberspace [7]; while the dawn of a new era of the immersive, interconnected 3D world appears possible thanks to a wave of revolutionary technologies like augmented reality (AR), virtual reality (VR), extended reality (XR), and virtual digital twins (DTs), these technologies also bring many new challenges and open problems before the comprehensive digital landscape of the metaverse becomes ubiquitous in daily life. Concerns exist for privacy and security that might be addressed with blockchain technology. Meanwhile, scalability is still among the top concerns [8].

Inspired by the vision of Metaverse and the hierarchical Edge-Fog-Cloud computing paradigm, a task- or application-oriented, local-scale immersive, interconnected 3D world is envisioned. The Microverse, a task-oriented, edge-scale, pragmatic solution for smart cities applications, is proposed, which involves IoT resources under multiple administration network domains. Instead of creating a Metaverse that mirrors the entire smart city in one digital world, each Microverse instance is a manageable digital twin of an individual network slice for a specific task. Following the edge-fog-cloud computing paradigm, Microverse enables on-site/near-site data collection, processing, information fusion, and real-time decision-making.

2. The Metaverse in the IoT: Challenges

In the context of smart cities, the fusion of the metaverse with the IoT—an expansive network of interlinked devices and sensors—heralds a transformative era in urban interaction, blending the digital with the physical [9]. The digital–physical synergy enriches the smart city landscape with immersive, interactive, and data-intensive environments. Yet, integrating the metaverse within the complex IoT infrastructure of smart cities presents a set of formidable challenges that need to be addressed [10][11].

The primary challenge lies in bandwidth and *latency* constraints [12]. Applications within the metaverse necessitate substantial data rates and minimal latency to facilitate seamless, immersive experiences. However, IoT environments usually function on limited networks, which are potentially inadequate for these high demands. Addressing the communication gap to guarantee fluid and responsive interactions in the metaverse, especially within the confines of IoT infrastructures, is a pivotal technical hurdle necessitating the development of inventive approaches in network infrastructure and data transmission strategies.

Scalability emerges as a critical issue [13] in integrating the IoT and the metaverse. The IoT landscape, characterized by a continuously growing assortment of devices, sensors, and data sources, presents a complex data and network interaction volume challenge. Adapting the metaverse to efficiently manage the immense amount of data while maintaining scalability parallel to the IoT's expansion is a sophisticated engineering endeavor. It is crucial to achieve scalability without sacrificing performance quality.

Interoperability remains a significant challenge in IoT environments [14][15]. Devices produced by various manufacturers frequently employ distinct communication protocols and data formats, complicating their integration. Establishing a cohesive metaverse ecosystem that incorporates these heterogeneous devices while preserving interoperability is a challenging yet crucial task to ensure a seamless user experience.

Security and *privacy* are paramount concerns within the IoT realm, and integrating the metaverse into an ecosystem significantly escalates these risks [9]. The potential for unauthorized access to sensitive IoT data via metaverse applications poses serious threats. Ensuring the security of data and devices in this converged environment is a critical challenge. Notably, the amalgamation of IoT data with the metaverse could create comprehensive user profiles, triggering ethical and privacy issues. Striking an appropriate balance between offering personalized experiences and maintaining user privacy is an intricate and necessary task.

Integrating the metaverse into the real world presents additional challenges [9][16]. The ambitious endeavor to adopt a metaverse aims to connect digital and physical domains seamlessly, requiring accurate location tracking, sophisticated object recognition, and advanced sensor fusion [17]. These sensor exploitation technologies could ensure precise alignment with IoT data and devices, yet they represent complex and intricate tasks that must be meticulously addressed for a digital metaverse.

Last but not least, *energy efficiency* is paramount in IoT environments, especially those dependent on distributed battery-operated devices. The persistent data demands from metaverse applications can rapidly exhaust device batteries, underscoring an urgent need for energy-efficient communication strategies. Three emerging technologies that could provide efficiency include digital twins, network slicing, and blockchains.

3. Digital Twins

The concept of the digital twin was initially introduced in 2002 and subsequently documented by the National Aeronautical and Space Administration (NASA) [18]. A digital twin (DT) is a digital model that accurately represents the components and behaviors of a physical object or system [19]. Unlike a traditional simulation, a DT is not restricted to one particular process and can contain different procedures. Moreover, establishing the DT system ensures that data communication between virtual and physical objects is bidirectional and real-time. These characteristics of DTs enable simulation, analysis, and optimization in a broader range of system areas compared to a simulation.

At first, industrial manufacturing adopted DT technology mainly to enhance different stages of production through simulation, optimization, and the incorporation of machine learning technologies. An example is an event-driven simulation focusing on manufacturing and assembly jobs, utilizing digital twin technology and human–robot collaboration [20][21][22]. A proposed framework employs digital twin technology to enable accurate and multidisciplinary integration in assembly processes, particularly in industries that deal with high-precision products (HPPs) [23]. The HPP also develops a prediction and enhancement framework and a practical examination to validate its efficacy and practicality. The case study illustrates an ice cream machine as an application instance of a digital twin (DT) in the food industry [24], with a particular focus on the utilization of virtual reality (VR) and augmented reality (AR) technology for visualization and interaction purposes. The framework employs secure data transmission by implementing a secure gate between the computer and the cloud.

Recently, efforts have been demonstrated focusing on many facets of smart cities, such as intelligent transportation, intelligent energy distribution, and intelligent educational institutions. An example is the optimization problem in self-driving cars' electric propulsion drive systems (EPDSs) [25]. The suggested framework utilizes a DT-based approach to establish a connection between the logical twin in the control software and the propulsion motor drive system, enabling the estimation of EPDS performance. Nevertheless, the platform concepts are offered without any supporting experimental data. In another aspect of smart driving, a driver digital twin system was proposed that focused more on simulating and predicting the behavior mode and status of the drivers [26]. Compared to other work, the DT framework covers various aspects such as drivers' distraction detection, attention estimation, drowsiness detection, emotional state prediction, etc. Although the architecture is innovative, the paper did not provide any case studies or feasibility tests.

DT methods are also proposed to support environmental energy sustainability. The DT simulation methods and digital representation of the world mirror those of the dynamic data-driven applications systems (DDDAS) paradigm from the National Science Foundation in 2000 [27]. A DDDAS combines a digital simulation model with a physical estimation model to ensure runtime performance. The big data challenge is mitigated with the reduced order modeling and ensemble methods that afford systems-level performance and analysis. DDDAS methods were used to control wind turbines [28] and wind turbine farms [29]. Hence, for over a decade, there have been approaches to manage wind power plants by integrating DTs and cloud technologies with extensive data analysis to set up remote control stations [30].

DT techniques have been combined with blockchain; for example, a research team built a prototype of a smart campus [31][32]. With the help of a modeling engine, their system enables users to create their avatars inside the virtual campus. Users' location and primary status are reflected in real time. Moreover, an ecosystem with some simple functions, like a market, is established with the help of blockchain technology. As the purpose of the work mainly focused on social good, the authors did not further investigate the potential of the system.

In recent years, several healthcare applications have reconsidered the concept of DTs by incorporating living beings [33][34]. For example, a healthcare framework based on DTs is presented to monitor and predict an individual's health condition by utilizing wearable devices [35]. In addition, an innovative remote surgical prototype using VR, 4G, and AI is demonstrated, generating a patient's digital twin and enabling live surgery over a mobile network [36].

4. Network Slicing

Network slicing (NS) is an innovative and transformative idea within the telecommunications field, with the potential to significantly reshape the deployment and management of networks. Network slicing is a fundamental concept that entails the establishment of several virtual networks, referred to as *slices*, within a solitary physical network architecture [37]. Every individual slice is customized to fulfill distinct criteria, including bandwidth, latency, security, and other performance metrics, to accommodate the wide-ranging demands of different applications and services.

An NS strategy enables network operators to effectively manage resources and tailor services according to the distinct requirements of various use cases [38], such as massive machine-type communication (mMTC), ultrareliable low-latency communication (URLLC), and enhanced mobile broadband (eMBB). As an illustration, a network slice specifically designed for Internet of Things (IoT) devices may emphasize minimizing power consumption and ensuring extensive coverage. Conversely, a network slice tailored for augmented reality applications may prioritize minimizing latency and providing ample bandwidth.

Implementing network slicing plays a crucial role in facilitating the establishment of 5G networks, wherein various distinct and high-demand scenarios may operate together [39]. Operators can enhance network speed and responsiveness through the dynamic creation and management of slices, guaranteeing a smooth user experience across various applications.

Furthermore, network slicing facilitates the advancement of novel ideas and concepts by offering a dedicated environment for external developers and enterprises to generate and launch their services. The ability to adapt and change the network quickly facilitates the rapid progress of novel applications and services, stimulating economic expansion and technical innovation.

Ensuring security and isolation between slices are of utmost importance in network slicing. The NS architectural design integrates robust security procedures to mitigate interference and safeguard data privacy. The inclusion of NS into the metaverse is of utmost importance, mainly due to the coexistence of vital services like healthcare or autonomous cars with conventional mobile services inside the same network architecture.

5. Lightweight Blockchain

As the underlying technology of cryptocurrency, like Bitcoin [40], blockchain has been recognized as a critical technology to guarantee the assurance, security, and resilience of networked systems [41]. Blockchain is a distributed ledger technology (DLT) that utilizes cryptographic mechanisms, consensus protocols, and peer-to-peer (P2P) networks to ensure verifiable and auditable transition data storage. All participants in a blockchain network can agree on a transparent and immutable distributed ledger without relying on any third-party authority. Thanks to the system's properties like decentralization, immutability, and transparency, blockchain promises to improve security issues of centralized IoT frameworks, which are prone to single-point failures. Thus, shifting from centralized IoT systems to decentralized and secure IoT systems becomes realistic. Blockchain has been applied to IoT scenarios for security enhancement, like identity authentication [42], access control [43] and trust storage [44], and IoT data transacting [45]. Nevertheless, integrating cryptocurrency-oriented methods into IoT networks encounters challenges to performance, security, and scalability.

Various IoT–blockchain solutions have been reported recently by adopting lightweight blockchain design for IoT scenarios. By utilizing lightweight consensus protocols, like proof of stake (PoS) and practical Byzantine fault tolerance (PBFT), IoTChain [46] relies on a three-tier blockchain-enabled IoT architecture to guarantee security and efficiency. To improve scalability and interoperability, HybridIoT [47] leverages a hybrid blockchain architecture that allows a BFT-based mainchain framework to interconnect many proof-of-work (PoW) subchains. By combining a round-robin scheduling algorithm with consensus protocol, MultiChain has been implemented on a fog network to guarantee secure communication management for the Internet of Smart Things (IoST) [48]. As a lightweight blockchain architecture for general IoT systems, microchain [49] has been applied to diverse IoT applications, like federated learning atop hierarchical IoT networks [50] and urban air mobility (UAM) systems [41]. By dividing a blockchain into multiple vital components that can integrate with a lightweight consensus protocol and network model and optimize storage, microchain promises to handle the dynamicity and heterogeneity of the microverse.

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