Decentralized Cooperative Caching for Sustainable Metaverse via Meta Self-Supervision Learning

Ximing Chen, Jing Qiu, Fasheng Zhou, Hui Lu, Lejun Zhang, Zhihong Tian, Xiaojiang Du, and Mohsen Guizani

Abstract

Metaverse is a multidimensional virtual world that integrates digital twin space technology. It is an interactive and integrative process with the physical world, involving virtualization and digitization of the real world. The high demands of the metaverse on transmission latency, processing speed, and security pose significant challenges to network load. In this article, we study an online distributed caching model in the context of digital twin metaverse. With unknown file popularity, we elaborate a collaborative caching system to optimize the burst bit error rate of wireless transmission while satisfying the latency requirements in metaverse applications. Then, we propose a meta-based self-supervised learning algorithm that can jointly allocate caching resources among various small base stations (i.e., metaverse edge nodes) in a distributed manner. Notably, given the system heterogeneity due to the massive number of devices in the metaverse, we cleverly introduce a multi-exits mechanism for neural networks to cope with the strong demand for ultra-low latency in metaverse applications. The effectiveness of the proposed methods is verified by numerical simulations, which significantly improve the transmission efficiency compared with existing comparative methods, thus facilitating the development of green communication technologies. Therefore, these methods are of great relevance to the future development and application of metaverse.

Introduction

Against the background of the rapid development of digital technology and mobile communication technology, Metaverse, a holographic and immersive comprehensive ecosystem, has gradually become a new frontier of intelligent application development and research [1]. Metaverse not only realizes the seamless integration of the real world and the virtual world, but also reflects the information of the real world in the virtual world in a dynamic and real time way through the concept of digital twin (DT). It provides users with an interactive experience across time, geography, and cultural boundaries. Based on cutting-edge technologies, such as artificial intelligence, big data, blockchain, and cloud computing, metaverse provides a new platform. Let users simulate various behaviors in the real world in the virtual world, including but not limited to communication, work, study, and entertainment. Such an immersive experience needs to rely on technical support, such as ultra-high transmission rate, ultra-low latency of milliseconds, and strong data security. However, when the traditional network architecture faces the needs of massive data transmission and real-time interaction in the metaverse, it often reduces the resource utilization due to its inherent centralized architecture, bandwidth limitation, redundant data transmission and other factors, and cannot meet these high requirements [2]. This not only hinders the development of the metaverse, but also reduces the quality of experience for users.

In this context, edge caching technology shows its strong potential. As a scale up evolution of Content Delivery Networks (CDN), deploying cache nodes at the edge of the network helps to significantly reduce the data transmission distance, reduce energy consumption, and improve transmission efficiency. However, the mobile metaverse places more stringent demands on network performance than traditional wireless scenarios, covering large scale device connectivity, high performance end-to-end transmission latency, in network compute caching, and flexible access processing capabilities [3]. In particular, in terms of network wide ubiquitous caching requirements, each node in the metaverse is required to make accurate predictions of user data demand and solve the problems of collaborative management and data synchronization among nodes, which undoubtedly poses new challenges for caching technology [4]. On the other hand, the metaverse is a huge and constantly changing network environment, consisting of countless different types of devices, applications, services, and users. Facing this high degree of heterogeneity, it is also an important challenge for caching technology to make accurate data prediction and caching decisions based on different application requirements and network environments.

In response to the above challenges, this article considers a novel distributed edge caching scenario where the physical and virtual worlds interact

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with each other. And we study an online cooperative edge caching system to reduce transmission delay and error by coordinating caching policies to support applications in the metaverse and promote the practice of green communication technologies. Our main contributions are summarized as follows.

- A content centric framework for distributed online collaborative caching is proposed. It enables users to interact with other objects through their corresponding DT in the virtual world and obtain relevant data from the physical world caching network. The goal is to optimizing the allocation strategy of edge cache nodes and minimizing the average transmission burst bit error rate (BBER) of the entire network.
- To improve the convergence speed and generalization capability of the model, a decentralized meta-based self supervised learning (D-MSSl) algorithm is proposed to achieve fast adaptation and design caching policies in a time varying mobile metaverse.
- For the highly heterogeneous nature of the metaverse network system, a multi-exits mechanism DME-MSSL oriented to the D-MSSL algorithm to enable computationally weaker nodes to terminate training early and make caching decisions.

The rest of this article is mainly organized as follows: In the next section, we discuss the optimization challenges of content centric edge caching and related work on centralization and decentralization. Subsequently, we describe our proposed online decentralized cache allocation framework and provide the detailed system design. Consequently, a deep model multi-exit mechanism is introduced. The numerical simulation that verifies the feasibility of the proposed framework is then reported. Finally, we summarize the study in the conclusion section.

Preliminaries

We review the research of edge cache technology based on optimization algorithm and deep learning. Then, we discussed some classic edge caching mechanisms.

Related Works

For the positive caching problem, the main optimization objectives are cache hit ratio and cumulative transfer delay. Krishnan *et al.* [5] studied the impact of retransmissions on hit rate in static and dynamic user scenarios, and analyzed cache balance in mobile user scenarios. In addition, the optimization of cumulative transmission delay is also a major research perspective. For example, Yu *et al.* [6] model the cache replacement process as a many-to-many matching game and minimize transmission delay by adjusting the overall cache decision.

Given the increasing complexity of mobile networks, AI techniques are now being utilized to optimize wireless communications. AI has gradually achieved human level performance, especially with large amounts of data. Mehrizi *et al.* [7] proposed an online collaborative caching algorithm based on a probabilistic dynamic model, using the Variational Bayes approach for estimating the model parameters. In the context of the huge amount of information in the metaverse, the centralized algorithm brings a huge computing and transmission burden to the cloud, which is not conducive to the development of green communication. In comparison, the distributed system provides a more efficient solution for metaverse related applications using edge caching technology, which can significantly improve response speed, reduce transmission delay, and improve energy efficiency. For the popularity of files unknown, the research uses an online distributed algorithm to coordinate with SBSs in a wireless network. Xu and Tao [8] proposed a calibration algorithm to predict the caching strategy of neighboring SBSs, and each SBSs uses a multi-agent multi-armed bandit algorithm to determine the caching strategy which will still introduces additional complexity.

Recent research work has involved edge caching technology in metaverse scenarios. Cai *et al.* [9] designed an efficient control strategy that can integrate computing, caching and communication (3C) resources, and implemented the strategy by implementing multi-pipeline flow control and 3C resource scheduling mechanism. To further optimize the online delivery performance of data intensive services, this study also proposes a database placement strategy based on throughput maximization, and two effective database replacement strategies. On the other hand, Huynh *et al.* [10] proposes an innovative DT solution combining mobile edge computing (MEC) and ultra-reliable low latency communication (URLLC), aiming to provide support for metaverse applications. From the perspective of the 3C integration model, the solution optimizes the edge caching strategy, task offloading strategy, and the allocation of computing and communication resources to solve the optimal problem of delay in the metaverse enabled by DTs. However, while latency is seen as an important performance metric in Metaverse applications, it is not the only consideration. In many metaverse applications, the correct transmission of data is also critical, so the importance of transmission errors cannot be ignored. However, current research efforts have not adequately considered this important aspect.

Edge Caching Mechanism

Edge caching technology has gone through multiple technical stages from CDN based to cloud computing based to metaverse based. From the initial static content caching, after several technical iterations, it has become dominated by caching dynamic content, such as AR/VR applications and real time streaming video in the metaverse, continuously improving network speed and application response speed. We briefly review some of the classic edge caching mechanisms as follows.

Cooperative Caching: This is a wireless edge caching technique that allows multiple caching nodes (e.g., base stations or user devices) to work together and share their caching resources to improve caching efficiency and system performance. By coordinating caching policies, caching resources can be better utilized, content delivery latency can be reduced, and overall network throughput can be improved;

Content Central Caching: In this caching mechanism, content is selected and placed based on the properties of the content itself, such as its popularity, size, or lifecycle. This strategy can significantly improve cache utilization and reduce network congestion due to frequent requests for popular content.

Edge caching technology has gone through multiple technical stages from CDN based to cloud computing based to metaverse based. From the initial caching of static content, after many technical falls, it can cache dynamic content, such as AR/VR applications and real time streaming video in the metaverse, continuously improving network speed and application response speed.

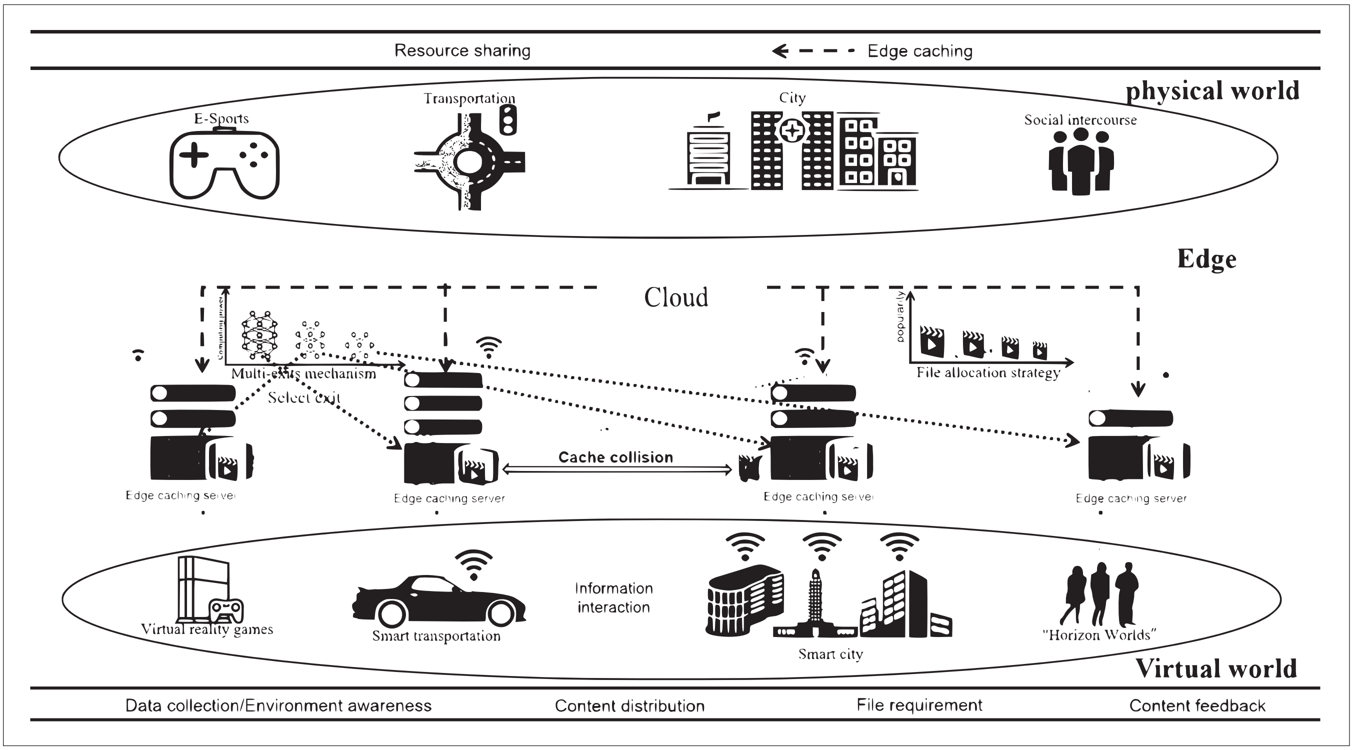

FIGURE 1. Metaverse model of the edge caching system.

User Quality Aware Caching: This caching mechanism focuses on the quality of the user experience. It uses machine learning and data mining techniques to predict user behavior and needs, and optimizes caching decisions accordingly. This ensures that the most relevant and desired content is always available, thus increasing user satisfaction.

Wireless Environment Adaptive Caching: This caching mechanism considers the characteristics of the wireless environment, such as dynamic changes in bandwidth and signal propagation loss. It adjusts the caching policy based on the current state and future trends of the wireless network, enabling caching decisions to adapt to changes in the network environment, thereby improving network performance.

However, for challenges, such as the convergence of physical and virtual worlds in the metaverse, dynamic content and real time requirements, complex user behavior modeling, and highly heterogeneous network architectures, it is clear that traditional caching mechanisms cannot fully meet the needs. Therefore, in the next discussion, we introduce an Innovative DT based metaverse mobile edge caching system that fully considers virtual real convergence and network heterogeneity, and propose an online collaborative caching resource allocation method that can quickly adapt to new scenarios, aiming to provide green and sustainable Quality of Service (QoS) guarantees for metaverse users.

System Model

Metaverse Model

In this article, we will explore a particular distributed edge caching scenario that contains two levels of interaction: the physical world and the virtual world, as shown in Fig. 1. The physical world includes wireless networks and various physical devices, whereas the virtual world serves as the DT of this reality, simulating and extending the behavior of the physical world. In the physical world, data collection and environment sensing are performed by various metaverse sensing devices, including the collection of static environmental data, dynamic wireless channel information, and user interaction information. In the virtual world, the user's DT is interacting with a series of virtual objects that exist in the form of various data. When the user's DT needs access to data for some kind of interaction, a metaverse node in the physical world delivers the cached data and information to the user's device.

In the physical world, there are also M Small base station (SBS), that is, metaverse nodes equipped with multiple antennas, and N single antenna IoT sensors, which corresponds to the Edge in Fig. 1. To simplify the description, we refer to these IoT sensors as users in the following discussion. Each metaverse node has its own local service area, at the same time, its cache capacity is C. These users are randomly distributed in the service area of each metaverse node, which can only interact with the local metaverse node. Other wireless parameters we follow previous work [11], including deep fading channels and narrowband communication, and so on. In which each user is served in dedicated orthogonal carrier frequencies resource block by SBS such that there is no transmission interference. This assumption is applicable to heterogeneous small cell networks in 5G and beyond, where adjacent SBSs adopt different carriers or time slots to avoid communication interference.

Caching Model

In a content centric web environment like the metaverse, user needs exhibit a high degree of dynamism and diversity, especially in the consumption of resources such as multimedia files (e.g., videos and 3D virtual models) and lightweight edge intelligence algorithms. Notably, the popularity of these contents is often time sensitive, manifesting itself in changes over time. Therefore, we consider multiple content clustering with dynamic popularity as caching model: suppose a user requests content from a file library consisting of contents. After extensive research and analysis, the content popularity distribution is usually modeled as a Zipf distribution with the Zipf factor floating slightly, a common long tail probability distribution where a few header files have a high request probability while the other files have a relatively small request probability. In addition, for the sake of the experimental analysis simplicity and clarity, we consider that the file popularity does not change significantly over a long period of time, and the size of each file is uniformly regarded as 1.

We focus on a more practical edge caching scenario, where the content request spaces of all users are different. All users are divided into S clusters, and the content space size of users in each cluster is *F*, defined as f_s {1, 2, ..., *F*}. Taking a base station service area as an example, requesting users belonging to different clusters will randomly appear in the local service area and randomly request contents from their own content space. In addition, according to the specificity of different classes of users, we define different Zipf factors γ to indicate that different file clusters have different request probability distributions. We also consider the cache replacement problem of SBS. According to the characteristics of the long tail of the Zipf distribution, we consider whether it is possible to replace only part of the content of the cache file in the case of limited traffic, and ensure that only the more important files are cached in the appropriate location. The results are presented subsequently.

Optimization Problem Formulation

In this section, we elaborate a collaborative caching framework in the context of DT metaverse. This framework further enhances the efficiency of content delivery through collaborative allocation of caching resources among all small base stations (SBSs), aiming to achieve the technical goal of green communication. Primarily, we set the optimization goal to minimize the burst error [11] of millimeter wave communication for the high speed, high fidelity, and high density of metaverse information transmission. In the narrowband communication scenario of the burst fading Rayleigh channel, physical layer parameters average fading duration (AFD) were introduced to evaluate the channel quality of the link between the user and the SBS. According to AFD, we deduce the BBER that causes a continuous bit error in deep fading channels. To adjust the caching strategy of each SBS according to the BBER, we define the optimization problem as minimizing the average BBER of the content delivered by the system.

Owing to limited capacity, each SBS can only cache partial files. Hence, cache cooperation among SBSs is vital. In the framework we consider, when a user requests a file, the response content received proceeds from the following three response methods:

- The local SBS caches the requested file, and the SBS-to-user BBER can be applied directly.
- If the local SBS does not cache the requested file, but an adjacent SBS does, the transmission has an extra distance, and a penalty factor μ is given to BBER, where $\mu > 1$.
- When neither the local SBS nor the adjacent SBS has the required files cached, we define a fixed b0 as the bit error rate transmitted from the central controller to the user, where BBER $\ll b_0$.

After considering the properties of the metaverse, we construct optimization equations based on three scenarios with the cache capacity as a constraint. Subsequently, we discuss two collaborative caching strategies at metaverse nodes: a full replacement strategy and a partial replacement strategy. First, we delve into a full replacement cache resource allocation scheme that aims to minimize the transmission error of the entire metaverse system. It is worth noting that frequent replacement of large numbers of files in a metaverse application would cause additional communication overhead, and for this reason we discuss a partial replacement strategy, adding a constraint that up to P cached contents can be replaced to maximize traffic efficiency and cost effectiveness.

Decentralized Multi-Exit Meta-Based Self Supervised Algorithm

In this section, we first propose a decentralized meta-based self-supervised learning framework to adapt to fast changing channels, that is, D-MSSL algorithm. Self-supervised learning is used to improve the prediction accuracy of the local cache revenue of the SBS. Combining the prediction of local SBS cache revenue and the historical cache information of adjacent SBSs, then the local SBS cache strategy was designed from a global perspective. To deal with system heterogeneity, a multi-exit mechanism is then proposed to select submodels with different network depths according to the computing power of edge devices.

Self-Supervision Learning

Self-supervised learning (SSL) is a classical machine learning method that does not require labels, whose core idea is to extract inherent information from unlabeled data, so as to design efficient supervision labels. Train model by using the characteristics of the data itself, the feature extraction and optimization ability of the model can be accurately improved, and it is more flexible than traditional supervised learning.

In this study, we are aiming to establish a unified evaluation standard for cache revenues, which involves recording the income of each content cached in each SBS and achieving independent training and prediction of cache revenue for each agent under non-cooperative conditions. The cache average channel gain is constructed based on the channel state and the popularity distribution of files. Specifically, we define the SSL label as the product of the inverse BBER of each user-SBS link and the file request probability in the observation time slot. We use the cache revenue of each file

Self-supervised learning (SSL) is a classical machine learning method that does not require labels, whose core idea is to design auxiliary tasks (pretext) to extract inherent supervisory information from a large amount of unsupervised data. By utilizing these constructed supervisory signals to train the network, valuable representations can be effectively learned for target classification tasks and beyond.

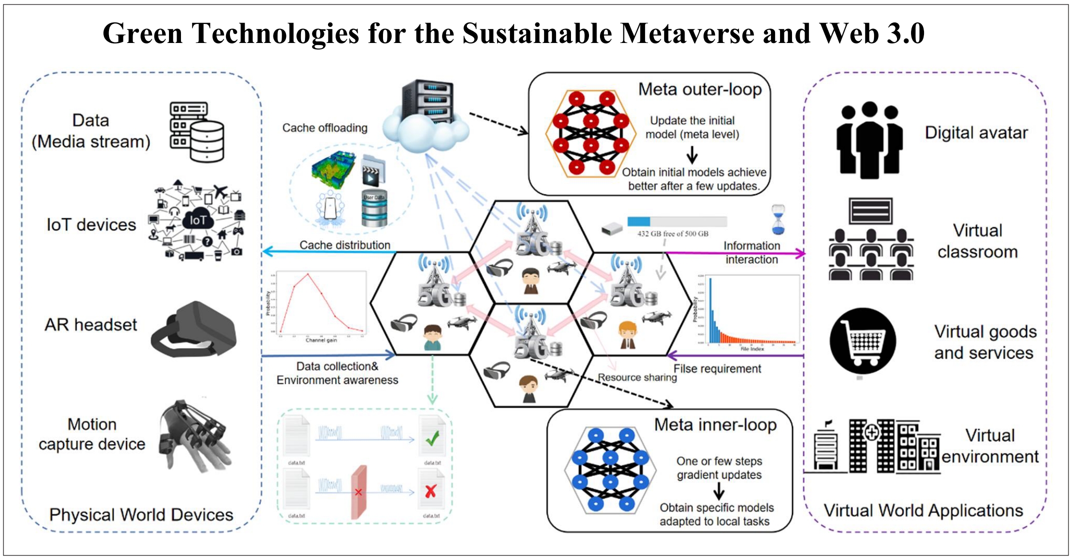

FIGURE 2. Proposed algorithm architecture.

as the output label of the model and train a deep learning model by continuously learning the model's own features to achieve accurate predictions of cache revenues. Since SSL does not require labeled samples, it can complete large scale model training without human intervention, thereby improving the scalability and practicality of the model. Note that the caching revenue here ignores cooperation. All SBSs share their historical cache information and design the caching policy by combining the former and the predicted caching revenues, which effectively avoids the cache collision [8]. The next section presents a D-MSSL algorithm that solves the formulated optimization problem.

Cooperative Caching Policy Decision Scheme

As each SBS predicts cache revenues for cached content in a decentralized manner, the label of the SSL algorithm is a unified measure of cache revenues served locally for each cache action. Thus, the model predictions only represent cached revenues that do not involve collaboration. Another important problem of the algorithm then becomes injecting cache cooperation into the model. In this subsection, we propose a cooperative cache allocation scheme for each SBS, which jointly determines the local SBS cache strategy according to the D-MSSL predicted value and the historical cache strategies of adjacent SBSs.

Each SBS predicts the caching revenue of each content without cooperation and broadcasts its own predicted revenue information and the caching strategy of the previous slot. When the file f is cached by the adjacent SBS$\tilde{m}$, the revenue of recaching the content to the local SBS m decreases. In predicting the file f, the revenue is subtracted by $1/\mu$ times the cache revenue of the SBS $\tilde{m}$ storage file f. On the contrary, when the adjacent SBS does not cache the file f, the prediction revenue for the file f increases because the SBS is radiated to the adjacent SBS. Finally, the SBS m selects the C files with the largest cache revenue as the cache strategy.

Proposed Algorithm

Consider the unique nature of the metaverse, such as highly personalized user behavior, rapidly changing environments, and the constant emergence of new applications. User behavior, needs, and applications can change rapidly with high uncertainty. It is necessary to employ more powerful and flexible machine learning algorithms to address these challenges. In our work, Model Adjacent Meta Learning (MAML) is introduced to combat the complex time-varying wireless environment [12]. MAML, as an algorithm adapted to few shot learning, is an indispensable key tool for dynamic, diverse and constantly emerging new application metaverse scenarios, enabling fast and effective learning on a very small number of samples. This algorithm allows each SBS to estimate local caching revenues and, in combination with a small amount of historical caching policy information from neighboring SBSs, independently design decentralized caching strategies.

As shown in Fig. 2, our proposed algorithm consists of two parts: an inner loop and an outer loop. The goal is to find a general initial network parameter that can achieve ideal performance with single step training across multiple similar task scenarios. In the inner loop, each SBS encounters communication scenarios that are considered as independent and related tasks. The SBS observes the time varying channel state information and performs one step gradient update using the constructed self-supervised labels, training a network model suitable for the local edge network, the sample set of which is considered as support set.

In the outer loop, each SBS sends its local model to the neighboring SBSs via broadcast after completing the inner loop update, and after receiving the network information broadcasted by the neighboring SBSs, the SBS further adjust and optimize the model parameters at the meta level. Specifically, each SBS aggregates the model parameters collected from neighboring SBSs after the inner loop, and calculates the gradient based on these aggregated parameters and initial network to achieve the update of the global initial parameters of the meta learning model.

Network Multi-Exit Mechanism

Due to the various types of devices and diverse applications involved in the metaverse, as well as the diversity of metaverse nodes, the metaverse

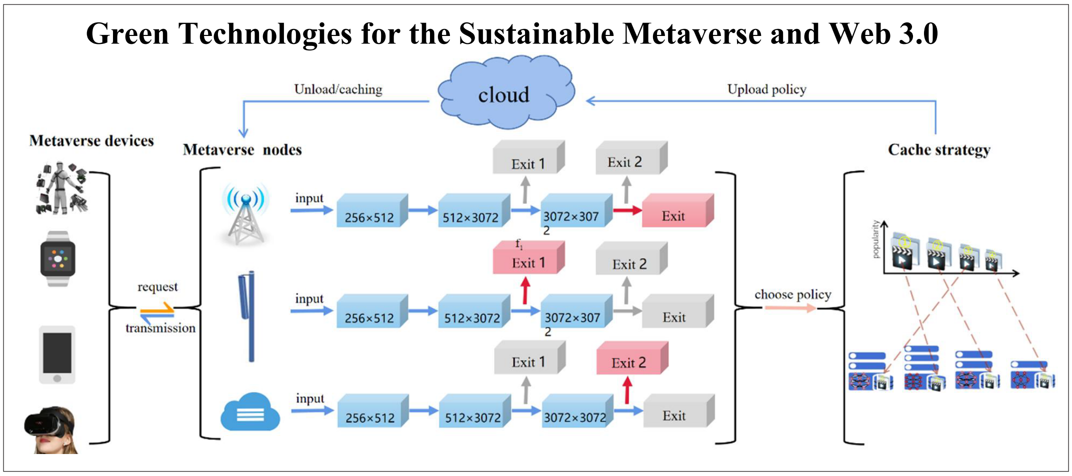

FIGURE 3. Neural network multi-exit mechanism.

network exhibits a high degree of systematic heterogeneity. To address this issue, we propose a multi-exit mechanism within the D-MSSL framework, named DME-MSSL. This mechanism enables devices with limited computational power to terminate training at earlier exits, thereby significantly enhancing the inference latency across various devices [13]. Using Multi-layer Perceptron (MLP) as an example, as show in Fig. 3, we have incorporated multiple exits at different layers of the model, which markedly differs from the conventional approach of only having an exit at the final layer of the neural network. This implies that we can obtain prediction results even prior to the completion of the computation in the final layer.

Numerical Results and Discussion

In the case study, we investigate the effectiveness improvement of DME-MSSL for online cache resource allocation tasks. Ten SBSs are considered, and for each SBS, the service area is a regular hexagon with a side length of 100 m, 5 classes of file sets with each file set containing 300 files, and each class contains 10 users. The transmission power of the SBS is 20 dBm, and the noise spectral density is –160 dBm/Hz. We refer to [14] and [15] to select the other simulation structure across various comparison algorithms to ensure the same computational complexity.

Figure 4 shows the performance comparison results of the proposed algorithm and the traditional pretrained algorithm. As can be seen from the figure, in the dynamic wireless channel environment, the convergence speed of the proposed algorithm is faster as the number of iterations increases. Moreover, the multi-exit mechanism affects the training effect to some extent, and the proposed DME-MSSL algorithm requires a period of training to converge. In comparison, there is a significant gap between the generalization capabilities of the pretrained algorithm and the proposed algorithm under the multi-exit mechanism. This result indicates that the proposed DME-MSSL algorithm has stronger generalization capabilities and can adapt more quickly to time varying channel scenarios.

Figure 5a, Fig. 5b and Fig. 5c compare the performance of various algorithms under the cache capacity of SBS, the file space of each cluster, and Zipf factor, respectively. After training with a few

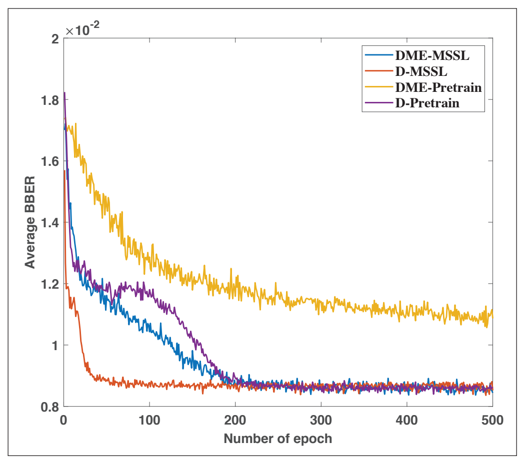

FIGURE 4. Average BBER for different training epochs.

samples (about 100 epochs), the average BBER of the D-MSSL algorithm is significantly lower than that of pretraining, and the performance gap becomes larger as the problem scale increases. It can also be seen that the performance of the proposed algorithm approaches that of the centralized algorithm; according to the analysis on the complexity, DME-MSSL saves a considerable number of computing resources and is more practical. Finally, Fig. 5d illustrates the partial replacement cache scenario. Considering data traffic from an economic perspective, it is unnecessary to completely replace the previous caching strategy. As storage capacity and computing resources are improved in the future, balancing the relationship between the number of cache replacement files and performance will be a highly practical and challenging open problem.

Conclusion

In this work, we propose a novel distributed edge caching framework that alleviates network congestion and enhances content delivery quality in DT metaverse scenarios by caching appropriate resources to the edge of the network. This not only delivers the necessary network capabilities for burgeoning technologies in diverse metaverse situations, VR, AR, and IoT, but also diminishes the energy usage for data transmission, in line with

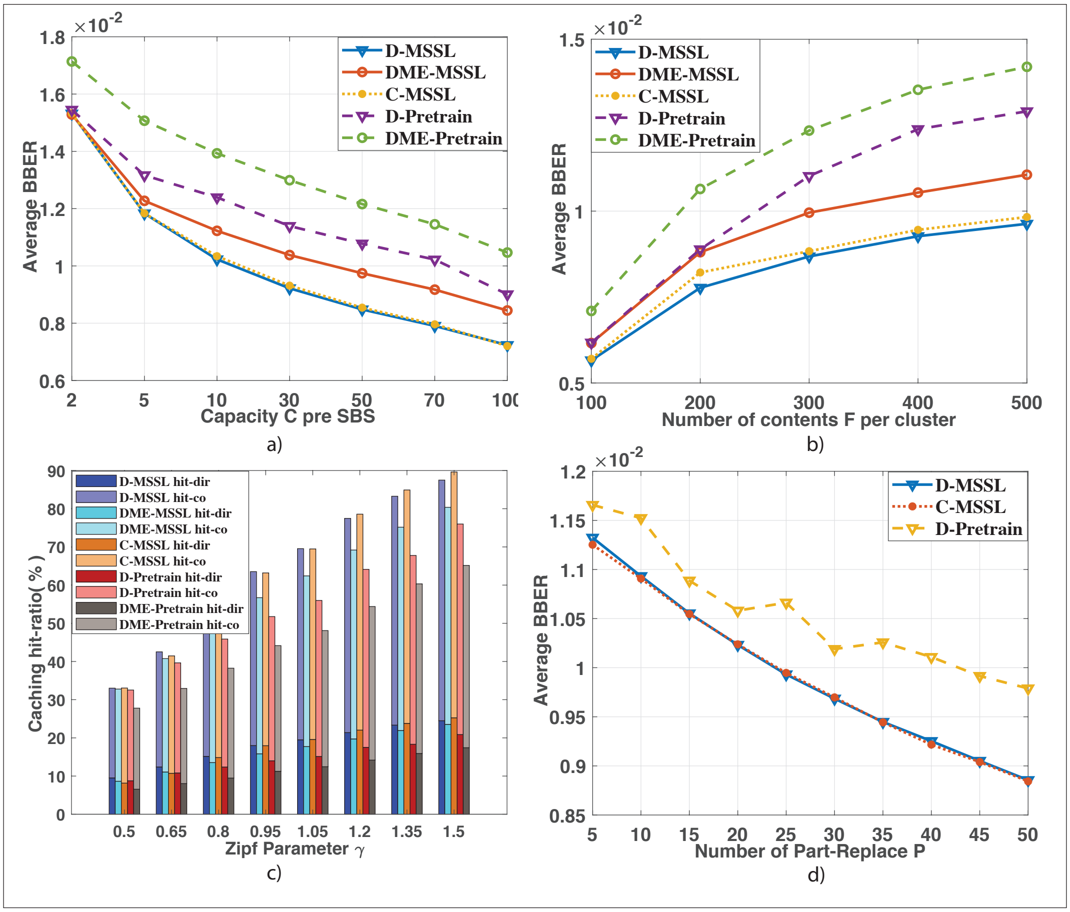

FIGURE 5. Comparison of the performance of the algorithms at different scales.

the concept of sustainable development of green communication technologies. On this basis, we proposed the D-MSSL algorithm, which achieves rapid adaptation and timely caching decision making in dynamic wireless scenarios. In addition, we utilize the multi-exit mechanism to solve the of system heterogeneity in Ad Hoc networks. Future research can further consider traffic utilization, response rate requirements, and dynamic network topology relationships to achieve joint optimization of caching decisions. This flexible and scalable edge network can more effectively meet the relevant needs of the metaverse.

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References

[1] F. Tang *et al.*, "The Roadmap of Communication and Networking in 6g for the Metaverse," *IEEE Wireless Commun.*, 2022, pp. 1–15.

[2] K. B. Letaief *et al.*, "The Roadmap to 6G: AI Empowered Wireless Networks," *IEEE Commun. Mag.*, vol. 57, no. 8, 2019, pp. 84–90.

[3] N. T. Hoa *et al.*, "Dynamic Offloading for Edge Computing-Assisted Metaverse Systems," *IEEE Commun. Letters*, 2023, pp. 1–1.

[4] Y. Cai *et al.*, "Compute- and Data-Intensive Networks: The Key to the Metaverse," *Proc. 2022 1st Int'l. Conf. 6G Networking*, 2022, pp. 1–8.

[5] S. Krishnan, M. Afshang, and H. S. Dhillon, "Effect of Retransmissions on Optimal Caching in Cache-Enabled Small Cell Networks," *IEEE Trans. Vehicular Technology*, vol. 66, no. 12, 2017, pp. 11,383–87.

[6] K. Yu *et al.*, "A Caching Strategy Based on Many-Tomany Matching Game in d2d Networks," *Tsinghua Science and Technology*, vol. 26, no. 6, 2021, pp. 857–68.

[7] S. Mehrizi *et al.*, "Online Spatiotemporal Popularity Learning via Variational Bayes for Cooperative Caching," *IEEE Trans. Commun.*, vol. 68, no. 11, 2020, pp. 7068–82.

[8] X. Xu and M. Tao, "Decentralized Multi-Agent Multi-Armed Bandit Learning With Calibration for Multi-Cell Caching," *IEEE Trans. Commun.*, vol. 69, no. 4, pp. 2457–72, 2021.

[9] Y. Cai *et al.*, "Joint Compute-Cachingcommunication Control for Online Data-Intensive Service Delivery," 2022.

[10] D. Van Huynh *et al.*, "Edge Intelligence-Based Ultra-Reliable and Low-Latency Communications for Digital Twin-Enabled Metaverse," *IEEE Wireless Commun. Letters*, vol. 11, 2022.

[11] X. Chen, F. Zhou, and D. Tang, "Caching in Narrow-Band Burst-Error Channels via Meta Self-Supervision Learning," *IEEE Commun. Letters*, 2022, pp. 1–1.

[12] T. Hospedales *et al.*, "Meta-Learning in Neural Networks: A Survey," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 44, no. 9, 2022, pp. 5149–69.

[13] F. Dong *et al.*, "Multi-Exit Dnn Inference Acceleration Based on Multidimensional Optimization for Edge Intelligence," *IEEE Trans. Mobile Computing*, 2022, pp. 1–1.

[14] W. Wang *et al.*, "Footstone of Metaverse: A Timely and Secure Crowdsensing," *IEEE Network*, 2023, pp. 1–8.

[15] F. Zhou *et al.*, "Edge Caching in Multi-UAV-Enabled Radio Access Networks: 3D Modeling and Spectral Efficiency Optimization," *IEEE Trans. Signal and Information Processing over Networks*, vol. 6, 2020, pp. 329–41.

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