

Resource Allocation and Resolution Control in the Metaverse with Mobile Augmented Reality

Peiyuan Si¹, Jun Zhao¹, Huimei Han^{1,2}, Kwok-Yan Lam¹, Yang Liu^{1,3}

¹School of Computer Science & Engineering, Nanyang Technological University, Singapore

²College of Information Engineering, Zhejiang University of Technology, Hangzhou, Zhejiang, P.R. China

³School of Information and Communication Engineering, Dalian University of Technology, Dalian, China

peiyuan001@e.ntu.edu.sg, {junzhao, huimei.han, kwokyan.lam}@ntu.edu.sg, yangliu_613@dlut.edu.cn

Abstract—With the development of blockchain and communication techniques, the Metaverse is considered as a promising next-generation Internet paradigm, which enables the connection between reality and the virtual world. The key to rendering a virtual world is to provide users with immersive experiences and virtual avatars, which is based on virtual reality (VR) technology and high data transmission rate. However, current VR devices require intensive computation and communication, and users suffer from high delay while using wireless VR devices. To build the connection between reality and the virtual world with current technologies, mobile augmented reality (MAR) is a feasible alternative solution due to its cheaper communication and computation cost. This paper proposes an MAR-based connection model for the Metaverse, and proposes a communication resources allocation algorithm based on outer approximation (OA) to achieve the best utility. Simulation results show that our proposed algorithm is able to provide users with basic MAR services for the Metaverse, and outperforms the benchmark greedy algorithm.

Index Terms—Metaverse, resource allocation, mobile augmented reality, outer approximation

I. INTRODUCTION

The development of blockchain and communication techniques motivated intensive interest in the Metaverse, which is considered a next-generation Internet paradigm [1]–[3]. Attracted by the potential of the Metaverse, many governments and companies around the world are planning and preparing for the upcoming Metaverse era; e.g., South Korea is promoting lessons based on the Metaverse, Facebook announced that it would become a Metaverse company and renamed itself as Meta, and Tencent has invested in an AR platform called “Avakin life” [4]–[6].

Current challenges. One of the key issues in the Metaverse is to connect the virtual world and the real world with the support of extend reality (XR), including virtual reality (VR) and augmented reality (AR) [7]–[10]. Current research on the Metaverse mainly focuses on solving the problem of communication and computation for VR to provide users with immersive experience [11], [12]. However, mobile VR services require extremely high data rate, which is not easy to achieve even under the context of 5G. Besides, VR users suffer and have to bear with the high

weight of current VR devices, which is another problem to be solved.

Mobile augmented reality (MAR) is a possible alternative option for VR, and also an important component of the Metaverse [13]–[16]. Compared to VR, MAR combines reality and the virtual world rather than creating a fully virtual world, which saves communication and computational cost [17]–[19]. Besides, current AR devices have a significant advantage over VR in weight, making them more comfortable and safer as wearable devices. AR also has its unique advantage in some applications, e.g., navigation, health care, tourism, shopping and education, where the interaction with reality is required [20]–[22].

Related work. Although AR requires lower data rate than VR, efficient allocation of communication resources is still necessary due to the massive number of users and devices connected to the Metaverse server. To improve the communication resource efficiency and quality of service (QoS), MEC and reinforcement learning (RL) for VR/AR service have attracted much attention [23]–[29]. Feng *et al.* [28] proposed a smart VR transmission mode scheme based on RL to optimize the D2D system throughput and achieve a balance between performance and resource efficiency. Chen *et al.* [23] introduced an RL-based energy-efficient MEC framework for AR services with task offloading and resource allocation to release the burden at the terminal. A recent work [30] applies deep RL to MAR services of the metaverse over 6G wireless networks. Resolution control is also one of the solutions to improve resource efficiency [31]. Higher resolution brings better QoS at the cost of occupying more communication resources while lower resolution improves resource efficiency. Thus, finding the balance between QoS and communication resources such as power and bandwidth is of vital importance to Metaverse MAR service.

In this paper, we propose an MAR-based Metaverse model with resolution control and resource allocation algorithm. In our proposed resource allocation optimization problem, both QoS and power consumption are included in the utility function for the balance between user experience and the energy efficiency of the service provider. To solve the mixed-integer nonlinear programming (MINLP) optimization problem, we propose a resource allocation algorithm based on outer approximation

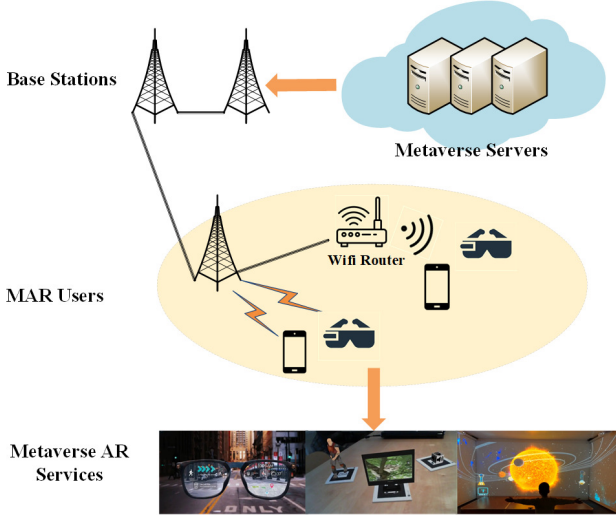


Fig. 1. System model of the Metaverse with mobile augmented reality.

(OA), which guarantees global optimum. Simulation results show that our algorithm is able to maximize the utility with given communication resources, and outperforms the benchmark greedy algorithm.

Contributions. The contributions of this paper are as follows:

- A MAR-based Metaverse model is proposed for applications where interaction with reality is required.
- A resolution control and resource allocation optimization problem for Metaverse MAR services is proposed and solved by an OA algorithm.
- Simulation of the proposed algorithm is implemented with the comparison to a benchmark greedy algorithm under various parameter settings. The results show the advantage of our proposed algorithm and the feasibility of the proposed Metaverse MAR service model.

The rest of this paper is organized as follows. Section II introduces the proposed system model. The problem formulation and solution are presented in Section III and Section IV respectively. Section V shows the simulation results and the corresponding explanation. The conclusion of this paper is discussed in Section VI.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In our proposed Metaverse MAR service model, we consider MAR service for multiple users supported by a base station in a particular area, which is connected to Metaverse servers. As shown in Fig. 1, MAR users can get Metaverse services with data synchronized to their avatars in the Metaverse while interacting with the real world with the support of the base station, which controls the MAR service quality by switching the resolution, e.g., 480P, 720P, 1080P. Due to the limit of total transmission power, the base station needs to dynamically allocate power for

users and control the resolution of MAR service according to the channel condition to achieve the best utility.

We assume that the base station provides N users with MAR service through N channels. With fixed bandwidth and limited transmit power, the base station allocates transmit power to N users, and the transmission rate for user n is given by

$$r_n = B \log_2 \left(1 + \frac{p_n g_n}{\sigma^2} \right), \quad (1)$$

where B and p_n denotes the bandwidth and transmit power for user n respectively, and σ^2 denotes the power of Gaussian noise. g_n denotes the channel gain between base station and user n . Let $\mathbf{p} := [p_1, p_2, \dots, p_N]$. The base station is able to provide users with different resolutions of MAR service according to the channel condition. The required transmission rate for real time MAR service is denoted by

$$C_n \in \{C_1, C_2, C_3\}, \quad (2)$$

where C_1, C_2, C_3 denote the required transmission rate of 360P, 720P and 1080P MAR service respectively. The base station can provide each user with only one type of service, and the selection indicator is given by

$$\mathbf{I} = \{I_{n,1}, I_{n,2}, I_{n,3} | n \in [N]\}, \quad (3)$$

where $I_{n,1}, I_{n,2}, I_{n,3} \in \{0, 1\}$, $\sum_{i=1}^3 I_{n,i} = 1$ and $[N] := \{1, 2, \dots, N\}$. To evaluate the quality of service (QoS) for users with given service selection, we introduce a QoS factor Q_n , which is given by

$$Q_n = \left(\frac{C_n}{R_{th}} \right)^\gamma = \sum_{i=1}^3 I_{n,i} \left(\frac{C_i}{R_{th}} \right)^\gamma, \quad (4)$$

where R_{th} denotes the constant reference service quality, and γ denotes the exponential factor of QoS. The best QoS is given by

$$Q_0 = \left(\frac{C_3}{R_{th}} \right)^\gamma, \quad (5)$$

QoS only evaluates the experience of individual user, which does not fully represent the utility of the resource allocation scheme. If the base station provides more users with higher QoS under given bandwidth resource, more power will be occupied to reach the required transmission rate. Thus, we take the total power consumption into consideration for the utility function, which is given by

$$U = (1 - \lambda - \mu) \eta_q \sum_{n=1}^N Q_n - \lambda \eta_p \sum_{n=1}^N p_n + \mu \eta_r \sum_{n=1}^N \Delta r_n, \quad (6)$$

$$\Delta r_n = \sum_{i=1}^3 C_i I_{n,i}^{(0)} - B \log_2 \left(1 + \frac{p_n g_n}{\sigma^2} \right), \quad (7)$$

where $\eta_q = (NQ_0)^{-1}$, $\eta_r = C_2^{-1}$ and $\eta_p = P^{-1}$ are normalization factors, λ , μ and $1-\lambda-\mu$ denote the levels of concern for energy consumption, redundancy of transmission rate and QoS respectively. We consider the redundancy of transmission rate as a positive factor because it provides robustness against the turbulence of channel. To maximize the utility of the resource allocation scheme under given total transmission power limit, the optimization problem is given by

$$\begin{aligned}
 P1 : \min_{\mathbf{I}, \mathbf{p}} \quad & \lambda \eta_p \sum_{n=1}^N p_n - \mu \eta_r \sum_{n=1}^N \Delta r_n - (1-\lambda-\mu) \eta_q \sum_{n=1}^N Q_n \\
 \text{subject to} \quad & \\
 \text{Con1} : \quad & \sum_{i=1}^3 C_i I_{n,i}^{(0)} - B \log_2 \left(1 + \frac{p_n g_n}{\sigma^2} \right) \leq 0, \forall n \in [N], \\
 \text{Con2} : \quad & \sum_{n=1}^N p_n \leq P, \\
 \text{Con3} : \quad & \sum_{i=1}^3 I_{n,i} = 1, \forall n \in [N], I_{n,i} \in \{0, 1\}, \quad (8)
 \end{aligned}$$

where constraint *Con1* indicates that data transmission rate should meet the requirement of the selected service quality. Constraint *Con2* denotes the total power constraint, and constraint *Con3* indicates that the base station can provide each user with only one type of service. Problem *P1* is a mixed-integer nonlinear programming (MINLP) problem, which can be solved by outer approximating (OA) method. The solution of *P1* is presented in Section IV.

III. PROBLEM SOLUTION

The MINLP problem *P1* can be solved by OA method in different steps, which are explained in the subsections below.

A. Solve the Nonlinear Programming Problem with Given Integer Variables

At the beginning of the OA algorithm, i.e., the first iteration, we give initial values to the integer variables matrix \mathbf{I} in the feasible region, which are denoted as $\mathbf{I}^{(0)}$. Then substitute $\mathbf{I}^{(0)}$ into *P1* to formulate the nonlinear programming problem *P1.1*, which is given by

$$\begin{aligned}
 P1.1 : \min_{\mathbf{p}} \quad & \lambda \eta_p \sum_{n=1}^N p_n - \mu \eta_r \sum_{n=1}^N \Delta r_n - A_1 \\
 \text{subject to} \quad & \\
 \text{Con4} : \quad & B \log_2 \left(1 + \frac{p_n g_n}{\sigma^2} \right) - \sum_{i=1}^3 C_i I_{n,i}^{(0)} \geq 0, \forall n \in [N], \\
 \text{Con5} : \quad & P - \sum_{n=1}^N p_n \geq 0, \quad (9)
 \end{aligned}$$

where the constant A_1 is given by

$$A_1 = (1-\lambda-\mu) \eta_q \sum_{n=1}^N \sum_{i=1}^3 I_{n,i}^{(0)} \left(\frac{C_i}{R_{th}} \right)^2. \quad (10)$$

With given integer variables, problem *P1* is transformed into nonlinear programming (NLP) *P1.1*, which can be solved by interior point method, whose worst case iteration complexity in this paper is $O(\sqrt{n} \log n \log \frac{n}{\epsilon})$ [32].

We introduce an auxiliary variable s_n to reformulate the problem as

$$\begin{aligned}
 P1.2 : \min_{\mathbf{p}} \quad & \lambda \eta_p \sum_{n=1}^N p_n - \mu \eta_r \sum_{n=1}^N \Delta r_n - A_1 \\
 \text{subject to} \quad & \\
 \text{Con4} : \quad & B \log_2 \left(1 + \frac{p_n g_n}{\sigma^2} \right) - \sum_{i=1}^3 C_i I_{n,i}^{(0)} = s_n, \forall n \in [N], \\
 \text{Con5} : \quad & P - \sum_{n=1}^N p_n \geq 0, \\
 \text{Con6} : \quad & s_n \geq 0, \forall n \in [N]. \quad (11)
 \end{aligned}$$

The barrier function is given by

$$\begin{aligned}
 J(p, \tau) = & \lambda \eta_p \sum_{n=1}^N p_n - \mu \eta_r \sum_{n=1}^N \Delta r_n - A_1 \\
 & - \tau \left(\log(s_n) + \log \left(P - \sum_{n=1}^N p_n \right) \right), \quad (12)
 \end{aligned}$$

where τ is a positive barrier parameter. The perturbed KKT conditions for $n \in [N]$ are given by [33]

$$\nabla J(p, \tau) - \Delta r_n z_n = 0, \quad (13)$$

$$\Delta r_n - s_n = 0, \quad (14)$$

$$s_n z_n = \tau, \quad (15)$$

$$s_n \geq 0, z_n \geq 0, \quad (16)$$

where $z_n, n \in [N]$ are Lagrange multiplier-inspired dual variables. The interior point method starts with a feasible point which satisfies the perturbed KKT conditions with small τ , and continue to find smaller τ . As the value of τ approaches zero, the solution is expected to converge to a point which satisfies the KKT point of problem *P1.1*.

With the obtained optimal power allocation, the solution of *P1.1* at t -th iteration is denoted as $z_{ub}^{(t)} \left(\mathbf{p}_{ub}^{(t)} \right)$, which is a lower bound of the global optimum, where $\mathbf{p}_{ub}^{(t)}$ denotes the optimal solution at the t -th iteration.

B. Solve the Mixed-integer Linear Programming Problem

After obtaining the optimal solution for P1.2, we formulate the first-order Taylor expansion of the original problem P1 at point $\mathbf{p}_{ub}^{(t)}$ as

$$\begin{aligned}
 P1.3 : \min_{\mathbf{I}, \mathbf{p}} \quad & \lambda \eta_p \sum_{n=1}^N p_n - \mu \eta_r \sum_{n=1}^N \left(A_2 - \sum_{i=1}^3 C_i I_{n,i} \right) \\
 & - (1 - \lambda - \mu) \eta_q \sum_{n=1}^N Q_n \\
 \text{subject to} \quad & \\
 \text{Con7} : \quad & A_2 - \sum_{i=1}^3 C_i I_{n,i} \leq 0, \forall n \in [N], \\
 \text{Con2, Con3}, \quad &
 \end{aligned} \tag{17}$$

where

$$A_2 = B \log_2 \left(1 + \frac{p_n^{(t)} g_n}{\sigma^2} \right) + \frac{B g_n}{\ln 2 (\sigma^2 + p_n^{(t)} g_n)} (p_n - p_n^{(t)}). \tag{18}$$

Problem P1.3 is a mixed-integer linear programming program (MILP), which can be solved by existing MILP solvers with branch-and-bound algorithm. As MILP problems are NP-hard, there are no polynomial complexity algorithms, and thus the complexity in the worst case is still exponential. However, the branch-and-bound algorithm reduces the average complexity compared to brute force search [34]. The precise estimation of branch-and-bound algorithm complexity requires the probability that a node in the branch-and-bound tree is optimal, which is hard to obtain in the optimization problem of this paper. To analyze the complexity of this algorithm, we implemented running time experiments which show acceptable results that the algorithm is able to converge within 30 seconds with CPU i7-9750H and 16GB memory.

The optimal solution of problem P1.3 at the t -th iteration is denoted as $z_{lb}^{(t)} \left(\mathbf{I}_{lb}^{(t)}, \mathbf{p}_{lb}^{(t)} \right)$, which is a lower bound of the global optimum.

C. Compare the Gap Between $z_{lb}^{(t)}$ and $z_{ub}^{(t)}$

As the lower bound and upper bound of global optimum are obtained, the gap between them is given by

$$G = \left| z_{ub}^{(t)} - z_{lb}^{(t)} \right|. \tag{19}$$

The algorithm is considered to be converged when $G \leq \epsilon$, where ϵ is a given precision factor. If $G \geq \epsilon$, substitute the integer variables $\mathbf{I}_{lb}^{(t)}$ into the original problem P1 for the next iteration. The overall algorithm is shown in Algorithm 1.

Algorithm 1 Outer Approximating Algorithm for Communication Resource Allocation in the Metaverse

Initialize: $t = 1$

Input: $\mathbf{I}^{(0)}$

Step 1.1: Substitute $\mathbf{I}^{(t-1)}$ into P1 to formulate nonlinear programming (NLP) problem P1.1

Step 1.2: Solve P1.1 by interior method to get lower bound $z_{ub}^{(t)} \left(\mathbf{p}_{ub}^{(t)} \right)$ of the global optimum

Step 2.1: Formulate the MILP problem P1.3 with the first-order Taylor expansion at point $\mathbf{p}_{ub}^{(t)}$

Step 2.2: Solve P1.3 by MILP solvers to get $z_{lb}^{(t)} \left(\mathbf{I}_{lb}^{(t)}, \mathbf{p}_{lb}^{(t)} \right)$

Step 3: If $G = \left| z_{ub}^{(t)} - z_{lb}^{(t)} \right| \leq \epsilon$, **Output:** $\{\mathbf{I}^{(t)}, \mathbf{p}^{(t)}\}$, **Else** Go to **Step 1.1**

TABLE I
CONSTANT PARAMETER SETTING

Parameter and Physical Meaning	Value
Exponential factor of QoS (γ)	2
Number of users (N)	5
Precision factor (ϵ)	10^{-3}
Bandwidth (B)	5MHz
Frequency (f)	28GHz (i.e., 5G spectrum)
Reference service quality (R_{th})	0.77Mbps
Power of Gaussian noise (σ^2)	5×10^{-8} W
Reference distance (d_0)	(5, 4, 3, 2, 1)(m)
Required transmission rates (C_1, C_2, C_3)	(0.77, 1.92, 3.84)(Mbps)

IV. SIMULATION RESULTS

In this section, we present the simulation results of the proposed OA-based resource allocation algorithm and the comparison with a benchmark greedy algorithm. In the simulation, the setting of constant parameters is given in Table I, and the benchmark greedy algorithm is given in Algorithm 2. The channel gain in simulation is set as

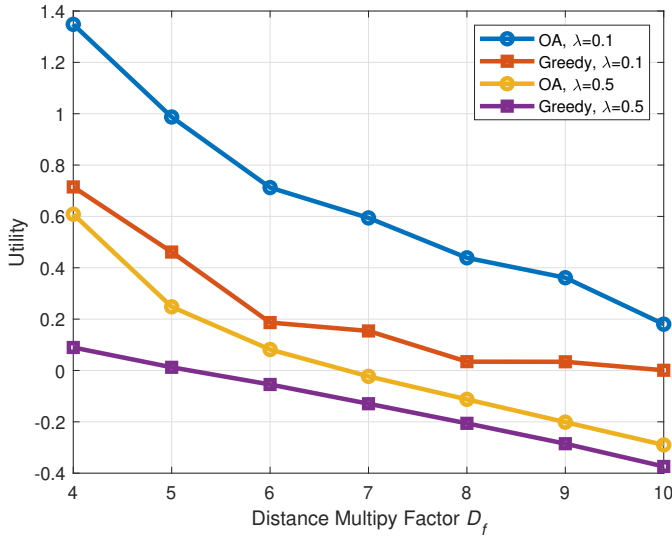
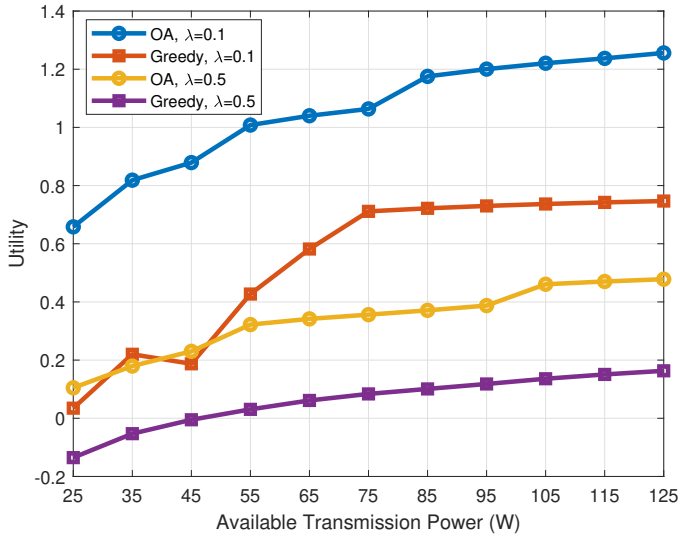
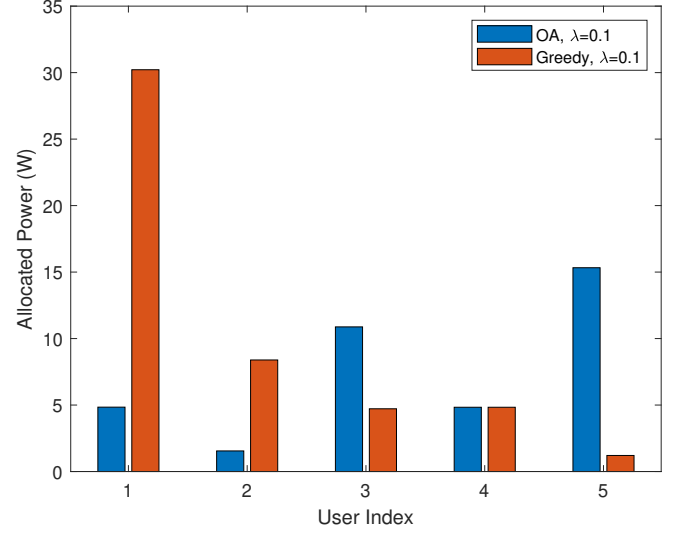
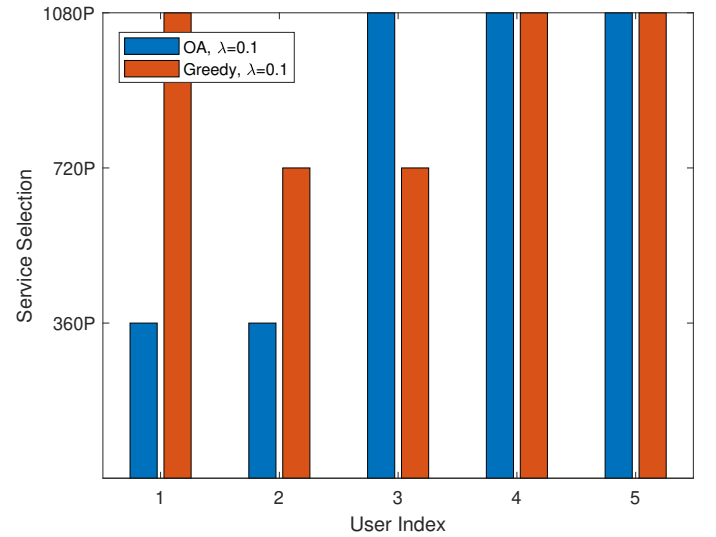
$$g_n = 20 \log_{10}(d_n) + 20 \log_{10}(f) - 147.55, \tag{20}$$

$$d_n = D_f d_0(n), \tag{21}$$

where $d_0(n)$ denotes the reference distance between base station and user n , and D_f denotes the distance multiply factor. The default value of μ is set to 0.1.

Fig. 2 shows the utility comparison between two algorithms with different D_f and λ . We can find that the utility of both algorithms decrease with increasing user-to-BS distance because the base station needs more power to provide the same service under smaller channel power gain. The OA algorithm outperforms the greedy algorithm in two different cases, i.e., $\lambda = 0.1$ and $\lambda = 0.5$, because it ensures global optimum while the greedy algorithm only obtains a local optimum.

Fig. 3 shows the utility comparison between two algorithms with different P and λ . The utilities of both algorithms increase as the total available transmission power P increases because

Algorithm 2 Benchmark Greedy Algorithm**Initialize:** $P_{rest} = P$, $U_{max} = -\infty$ **For** $n \leq N$ **For** $i \leq 3$ $I_{n,i}^{(t)} = 1$, $p_n^{(t)}$ = minimum required powerCalculate the utility U and remaining power P_{rest} under current selection**If** $U > U_{max}$ and $P_{rest} \geq 0$ Update $U_{max} = U$, $I_{n,i} = I_{n,i}^{(t)}$, $p_n = p_n^{(t)}$ **Output:** U_{max} , $I_{n,i}$, p_n Fig. 2. Utility comparison between two algorithms with different D_f and λ .Fig. 3. Utility comparison between two algorithms with different P and λ .Fig. 4. Power allocation with $\lambda = \mu = 0.1$, $D_f = 5$, $P = 50W$.Fig. 5. Service selection with $\lambda = \mu = 0.1$, $D_f = 5$, $P = 50W$.

less power is required for the same service, and the base station is able to provide users with better services and higher QoS. Fig. 3 also shows the greedy algorithm's ability to find the local optimum and the advantage of OA algorithm in more general cases due to the guarantee of the global optimum.

Fig. 4 and Fig. 5 show the power allocation and service selection under given $D_f = 5$, $\lambda = 0.1$ and $P = 50W$. The powers allocated by the greedy algorithm to users 1, 2 and 3 decrease as the index increase because the distances between the base station and users are $d_3 < d_2 < d_1$. As the distance decreases, the base station needs less power for basic 360P

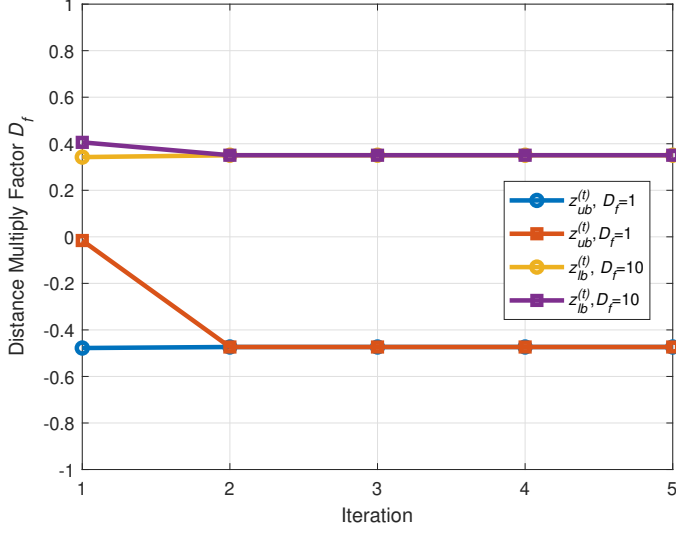
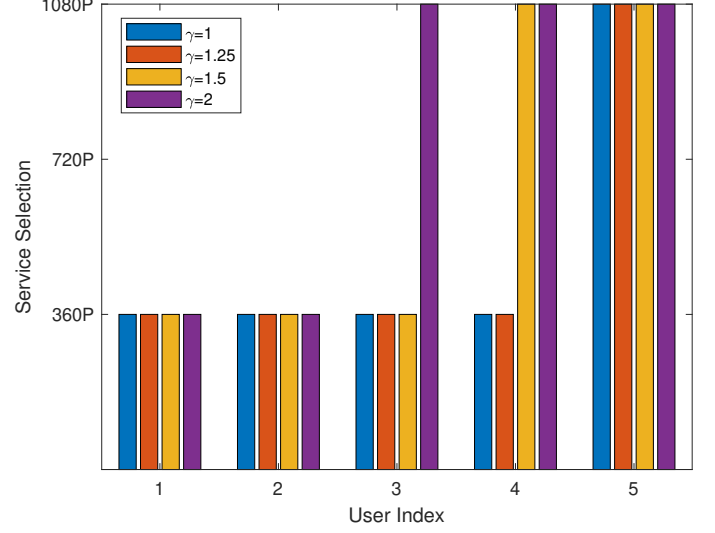


Fig. 6. Convergence of OA algorithm.

service. Due to the relatively poor channel condition of users 1, 2 and 3, it is expensive to improve the QoS of these three users. The OA algorithm results in a different policy for power allocation due to its consideration of robustness against channel turbulence, which is also shown in 5. Although user 1 and user 2 are assigned with same service quality, user 1 requires more power due to the longer distance to the base station, and it is the same case for user 3 and user 4. User 5 is assigned with large power because the robustness against channel turbulence contributes to the utility function.

Fig. 6 shows the convergence of the proposed OA algorithm for resource allocation under two different sets of parameters. We can find that the upper bound $z_{ub}^{(t)}$ and lower bound $z_{lb}^{(t)}$ converge within 5 iterations regardless of the parameter setting. In the simulation, we set the convergence threshold $\epsilon = 10^{-3}$ to limit the gap between $z_{ub}^{(t)}$ and $z_{lb}^{(t)}$, but in most cases the gap becomes zero after several iterations, which further guarantees the convergence.

Fig. 7 shows the influence of γ on service selection under $D_f = 5$, $P = 50W$, $\lambda = 0.1$, where the base station takes the power consumption as the main concern, and the power resource is adequate to provide all users with the best service. In this case, the exponential factor of QoS has a great influence on the policy decisions of the base station. With larger γ , the base station gets more benefit in utility through improving the QoS, and becomes more willing to provide the users with better service even if it gets more penalty from energy consumption. Thus, setting γ properly is critical to the balance between power consumption and QoS. As γ increases, the base station tends to improve QoS of the users with larger index first because they are closer to the base station than those with smaller index, which requires less power to achieve the same QoS.

Fig. 7. Influence of γ on service selection.

V. CONCLUSION

In this paper, we proposed a MAR-based Metaverse model for applications that require interaction with the real world. In order to maximize the utility of the base station, we formulate a resolution control and resource allocation optimization problem, and solve the MINLP problem with OA algorithm. The simulation results indicate that our proposed resource allocation algorithm outperforms the benchmark greedy algorithm due to the guarantee of global optimum. Our work also shows the feasibility of MAR to provide basic Metaverse service and the advantage of our proposed algorithm over benchmark greedy algorithm.

ACKNOWLEDGEMENT

This research/project is supported by the National Research Foundation, Singapore under its Strategic Capability Research Centres Funding Initiative. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of National Research Foundation, Singapore. This research/project is supported by the Ministry of Education, Singapore, under its Grant Tier 1 RG97/20, and Grant Tier 1 RG24/20; in part by the NTU-Wallenberg AI, Autonomous Systems and Software Program (WASP) Joint Project; and in part by the Singapore NRF National Satellite of Excellence, Design Science and Technology for Secure Critical Infrastructure under Grant NSoE DeST-SCI2019-0012. This work was also supported in part by National Natural Science Foundation of China under Grants 62001419 and 62131016, in part by Zhejiang Provincial Natural Science Foundation of China under Grant LQ21F010012. This work is also funded by Dalian University of Technology, China under Grant No. DUT20RC(3)029.

REFERENCES

- [1] M. Xu, D. Niyato, J. Kang, Z. Xiong, C. Miao, and D. I. Kim, "Wireless edge-empowered metaverse: A learning-based incentive mechanism for virtual reality," *arXiv preprint arXiv:2111.03776*, 2021.
- [2] Y. Han, D. Niyato, C. Leung, C. Miao, and D. I. Kim, "A dynamic resource allocation framework for synchronizing metaverse with iot service and data," *arXiv preprint arXiv:2111.00431*, 2021.
- [3] R. Cheng, N. Wu, S. Chen, and B. Han, "Will metaverse be nextg internet? vision, hype, and reality," *arXiv preprint arXiv:2201.12894*, 2022.
- [4] H. Ning, H. Wang, Y. Lin, W. Wang, S. Dhelim, F. Farha, J. Ding, and M. Daneshmand, "A survey on metaverse: the state-of-the-art, technologies, applications, and challenges," *arXiv preprint arXiv:2111.09673*, 2021.
- [5] S. M. Park and Y. G. Kim, "A metaverse: taxonomy, components, applications, and open challenges," *IEEE Access*, 2022.
- [6] B. Egliston and M. Carter, "Critical questions for facebook's virtual reality: Data, power and the metaverse," *Internet Policy Review*, vol. 10, no. 4, pp. 1–23, 2021.
- [7] L. H. Lee, T. Braud, P. Zhou, L. Wang, D. Xu, Z. Lin, A. Kumar, C. Bermejo, and P. Hui, "All one needs to know about metaverse: A complete survey on technological singularity, virtual ecosystem, and research agenda," *arXiv preprint arXiv:2110.05352*, 2021.
- [8] F. Hu, Y. Deng, W. Saad, M. Bennis, and A. H. Aghvami, "Cellular-connected wireless virtual reality: Requirements, challenges, and solutions," *IEEE Communications Magazine*, vol. 58, no. 5, pp. 105–111, 2020.
- [9] I. Akyildiz and H. Guo, "Wireless extended reality (xr): Challenges and new research directions," in *Journal Future and Evolving Technologies*. ITU, 2022.
- [10] C. Chaccour, M. N. Soorki, W. Saad, M. Bennis, and P. Popovski, "Can terahertz provide high-rate reliable low latency communications for wireless vr?" *IEEE Internet of Things Journal*, 2022.
- [11] Y. Zhou, C. Pan, P. L. Yeoh, K. Wang, M. El-kashlan, B. Vucetic, and Y. Li, "Communication-and-computing latency minimization for uav-enabled virtual reality delivery systems," *IEEE Transactions on Communications*, vol. 69, no. 3, pp. 1723–1735, 2020.
- [12] X. Liu, X. Li, and Y. Deng, "Learning-based prediction and proactive up-link retransmission for wireless virtual reality network," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 10, pp. 10 723–10 734, 2021.
- [13] Z. Huang and V. Friderikos, "Proactive edge cloud optimization for mobile augmented reality applications," in *2021 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE, 2021, pp. 1–6.
- [14] C. Bermejo and P. Hui, "A survey on haptic technologies for mobile augmented reality," *ACM Computing Surveys (CSUR)*, vol. 54, no. 9, pp. 1–35, 2021.
- [15] Q. Liu, S. Huang, J. Opadere, and T. Han, "An edge network orchestrator for mobile augmented reality," in *IEEE INFOCOM 2018-IEEE Conference on Computer Communications*. IEEE, 2018, pp. 756–764.
- [16] J. Grubert, T. Langlotz, S. Zollmann, and H. Regenbrecht, "Towards pervasive augmented reality: Context-awareness in augmented reality," *IEEE transactions on visualization and computer graphics*, vol. 23, no. 6, pp. 1706–1724, 2017.
- [17] Y. Siriwardhana, P. Porambage, M. Liyanage, and M. Ylianttila, "A survey on mobile augmented reality with 5g mobile edge computing: architectures, applications, and technical aspects," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 1160–1192, 2021.
- [18] M. Erol-Kantarci and S. Sukhmani, "Caching and computing at the edge for mobile augmented reality and virtual reality (ar/vr) in 5g," *Ad Hoc Networks*, pp. 169–177, 2018.
- [19] J. Ren, Y. He, G. Huang, G. Yu, Y. Cai, and Z. Zhang, "An edge-computing based architecture for mobile augmented reality," *IEEE Network*, vol. 33, no. 4, pp. 162–169, 2019.
- [20] N. Xi, J. Chen, F. Gama, M. Riar, and J. Hamari, "The challenges of entering the metaverse: An experiment on the effect of extended reality on workload," *Information Systems Frontiers*, pp. 1–22, 2022.
- [21] D. Buhalis and N. Karatay, "Mixed reality (mr) for generation z in cultural heritage tourism towards metaverse," in *ENTER22 e-Tourism Conference*. Springer, 2022, pp. 16–27.
- [22] C. Moro, C. Phelps, P. Redmond, and Z. Stromberga, "Hololens and mobile augmented reality in medical and health science education: A randomised controlled trial," *British Journal of Educational Technology*, vol. 52, no. 2, pp. 680–694, 2021.
- [23] X. Chen and G. Liu, "Energy-efficient task offloading and resource allocation via deep reinforcement learning for augmented reality in mobile edge networks," *IEEE Internet of Things Journal*, vol. 8, no. 13, pp. 10 843–10 856, 2021.
- [24] Y. Sun, Z. Chen, M. Tao, and H. Liu, "Communications, caching, and computing for mobile virtual reality: Modeling and tradeoff," *IEEE Transactions on Communications*, vol. 67, no. 11, pp. 7573–7586, 2019.
- [25] Q. Liu and T. Han, "Dare: Dynamic adaptive mobile augmented reality with edge computing," in *2018 IEEE 26th International Conference on Network Protocols (ICNP)*. IEEE, 2018, pp. 1–11.
- [26] F. Guo, F. R. Yu, H. Zhang, H. Ji, V. C. Leung, and X. Li, "An adaptive wireless virtual reality framework in future wireless networks: A distributed learning approach," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 8, pp. 8514–8528, 2020.
- [27] C. Wang, S. Zhang, Y. Chen, Z. Qian, J. Wu, and M. Xiao, "Joint configuration adaptation and bandwidth allocation for edge-based real-time video analytics," in *IEEE INFOCOM 2020-IEEE Conference on Computer Communications*. IEEE, 2020, pp. 257–266.
- [28] L. Feng, Z. Yang, Y. Yang, X. Que, and K. Zhang, "Smart mode selection using online reinforcement learning for vr broadband broadcasting in d2d assisted 5g hetnets," *IEEE Transactions on Broadcasting*, vol. 66, no. 2, pp. 600–611, 2020.
- [29] X. Liu and Y. Deng, "Learning-based prediction, rendering and association optimization for mec-enabled wireless virtual reality (vr) networks," *IEEE Transactions on Wireless Communications*, vol. 20, no. 10, pp. 6356–6370, 2021.
- [30] T. J. Chua, W. Yu, and J. Zhao, "Resource allocation for mobile metaverse with the Internet of Vehicles over 6G wireless communications: A deep reinforcement learning approach," in *8th IEEE World Forum on the Internet of Things (WFIoT)*, 2022.
- [31] J. Ahn, J. Lee, S. Yoon, and J. K. Choi, "A novel resolution and power control scheme for energy-efficient mobile augmented reality applications in mobile edge computing," *IEEE Wireless Communications Letters*, vol. 9, no. 6, pp. 750–754, 2019.
- [32] M. R. Peyghami and S. F. Hafshejani, "Complexity analysis of an interior-point algorithm for linear optimization based on a new proximity function," *Numerical Algorithms*, vol. 67, no. 1, pp. 33–48, 2014.
- [33] M. Mehrjoo, S. Moazeni, and X. Shen, "Resource allocation in ofdma networks based on interior point methods," *Wireless Communications and Mobile Computing*, vol. 10, no. 11, pp. 1493–1508, 2010.
- [34] N. Thakoor, V. Devarajan, and J. Gao, "Computation complexity of branch-and-bound model selection," in *2009 IEEE 12th International Conference on Computer Vision*. IEEE, 2009, pp. 1895–1900.