electronics

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AP Association Algorithm Based on VR User Behavior Awareness

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Abstract: With the rapid development of virtual reality (VR) technology, this paper proposes an access point (AP) correlation method based on VR user behavior awareness to address the problem of how current AP correlation methods only focus on the performance improvements of ordinary users and ignore the impact of VR user behavior on service quality. This paper analyzes the AP association method under the coverage scenario of a multi-access point (multi-AP) scenario environment and controls the performance improvement of VR user APs or APs under the access controller (AC) by association. Firstly, the VR network application scenario and system model were constructed, and secondly, the user behavior was sensed by analyzing the viewing habits of users. Then, the VR user association problem based on VR user behavior perception was transformed into a "many-to-many" matching problem between VR user devices and APs, and the generalized multidimensional multiple choice knapsack (GMMKP) model was established to solve the problem using the backpack problem theory; the suboptimal solution algorithm was selected to obtain the best VR user AP association strategy. The experimental results show by simulation that the proposed algorithm in this paper performed better in terms of the AP load balancing and average network download latency compared to the comparison algorithms.

Keywords: VR; AP association; behavior awareness; edge networks

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Citation: Ruan, J.; Wang, Y.; Fan, Z.; Sun, Y.; Yang, T. AP Association Algorithm Based on VR User Behavior Awareness. *Electronics* **2022**, *11*, 3542. https://doi.org/10.3390/electronics11213542

Academic Editor: Stefanos Kollias

Received: 28 September 2022
Accepted: 26 October 2022
Published: 30 October 2022

1. Introduction

With the further development of communication technology, most traffic in the global network is used for video services. Many public places are now using edge network architecture with the dense deployment of APs. This network architecture is designed to better meet the needs of the network in terms of capacity, coverage, and user experience, which helps realize the large-scale promotion of video services. At the same time, in order to better improve the experience performance of VR services, it is necessary to provide VR users with real-time access service quality assurance at the edge network (anytime and anywhere). For example, online virtual reality education scenarios, and metaverse service providers (MSPs) need to determine the bandwidth allocated to VR users to meet the access requirements in order to guarantee normal quality access to services, such as "metaverse" [1]. However, it has been found that user access networks with dense AP scenarios deployed without effective management will have a direct impact on the user experience [2].From this, we conclude that the association management of dense APs can also have a great impact on the network performance and the quality of VR services. Therefore, the AP association approach in the study for dense AP coverage scenarios is an important core of the study in this section.

For VR services, the bandwidth demand will be 4–5 times that of a traditional video, usually 50 Mbps for smooth playback of a VR 360-degree video at 4K resolution, and 200 Mbps when the definition is up to 8 K. The field of vision (FoV) streaming solution is proposed to reduce the user's demand for the network bandwidth by sending only the video streams from the field of view. Although, this solution has a certain effect on the reduction of network bandwidth demand, the current network still cannot fully meet the demand of

VR services. When faced with the inability to meet high bandwidth requirements, users may encounter problems, such as poor playback, degraded visual quality, and reduced responsiveness of viewport control. VR 360-degree video streaming can have a greater impact on user experience compared to standard streaming setups. Specifically, a mismatch between head movements and display changes in a VR environment can lead to vertigo and an inability to continue watching the video [3]. The number of head movements of VR users during viewing was found to have a significant impact on the number of downloaded but not played (i.e., wasted) clips [4].

Based on the above analysis, it can be concluded that in an access network with dense AP deployment, the association relationship between VR users and APs can have some impact on the user's access in the edge network. In this environment, how much effective bandwidth VR users actually obtain is mainly influenced by two factors, one from other users, i.e., the rate and association policy and other characteristics of other users, and one from the user itself, i.e., that user's own association policy. That is, the behavioral characteristics of VR users and the choice of all users of VR have a direct impact on the true effective bandwidth received by the AP. The VR users have strong competitive relationships with each other, resulting in a mutually constraining relationship between APs and VR users. Therefore, there is an urgent need to give solutions in a local area network (LAN) on how to control the association relationship between APs and VR users while considering the efficiency of both the network side and the VR user side. To this end, we analyzed the impact on the network when VR users are associated with APs compared to normal users. We also considered the limitations of the AP multi-rate and load balancing and took the average user download delay as the optimization target. The MMKP model was extended and analyzed, and a heuristic algorithm was proposed to construct a locally optimal solution to obtain the best AP association strategy for VR users. Simulation results show that this mechanism has better performance compared to AP association algorithms that do not fully consider user behavior.The original contribution of this paper involves research on dense AP coverage scenarios based on the VR user's behavior-aware AP association method.

1. The AP association policy considers the impact of VR users' behavioral actions on the VR association method and considers the differences between users accessing multiple APs (and, thus, determines the data transmission speed of user-associated APs to obtain the corresponding multi-rate matrix while also considering load balancing).
2. The user AP association problem is solved by an AP association algorithm that minimizes the average user download latency. A heuristic algorithm is proposed to solve the joint optimization problem of association, which balances the AP load and minimizes the average user download latency.
3. The simulation results show that the proposed method shows better results for both the average user download delay and load balancing metrics compared to the baseline algorithm.

The structure of this paper is as follows. Section 2 presents the related research work. Section 3 describes the edge network in a dense AP deployment scenario, and analyzes VR user behaviors on AP association and multi-rate and user load balancing. Section 4 presents the associative optimization problem with network delay minimization. Section 5 proposes the heuristic algorithm for solving associative joint optimization problems. Section 6 validates the performance of the proposed scheme through a simulation. Section 7 discusses the future trends of VR. Section 8 concludes the paper.

2. Related Work

2.1. VR 360-Degree Video Requirements Analysis

Typically, most studies at this stage only have singularly improved quality of service (QoS) on the user side, whereas networks and service providers need to understand the relationship between network conditions and VR service performance. Quality of experience (QoE) applications are efficiently and accurately mapped to the corresponding QoS network/communication system, which ensures overall end-to-end operation. Therefore, most current research on QoE evaluation methods for VR users has progressively focused on the optimization of network metrics [5–8]. the performance of VR services can be considered as an indicator for detecting and evaluating the network environment as well as for planning the network behavior to meet VR functionality. The current stage for the application of virtual reality is mainly based on a panoramic video presentation from the Huawei white paper; it is known that the current stage of VR users need a more ultra-high definition resolution than traditional video, 360-degree panoramic video of monocular resolution is usually dominated by 4K resolution, and the full-view resolution will reach 12K, which is 48 times the traditional 1080P video. Along with the gradual progression process of VR panoramic video, both computation (image processing and frame rendering) and communication (queuing and wireless transmission) delays are the main bottlenecks of VR systems. At the same time, the bandwidth demand that would be triggered during the transmission of viewpoint transitions would be higher than the steady-state bandwidth demand [9]. Thus, it can be seen that all phases of the actual VR service requirements face low latency, and high bandwidth data demands. As shown in Table 1.

Table 1. Summary of VR 360-degree video network application requirements.

Standard	Quasi-VR (No Immersion)	Entry Level VR (Partial Immersion)	Advanced VR (Deep Immersion)	Ultimate VR (Full Immersion)
Panoramic resolution	Full view 4 K 2D	Full view 8 K 2D	Full view 12 K 2D	Full view 24 K 3D
Bandwidth requirements	25 Mbps	100 Mbps	418 Mbps	2.35 Gbps
RTT Requirements	40 ms	30 ms	20 ms	10 ms
Packet loss requirements	1.4×10^{-4}	1.5×10^{-5}	1.9×10^{-6}	5.5×10^{-8}

2.2. VR 360-Degree Video Association Strategy

Most of the current research has been conducted on the association strategy between APs and user terminals under edge networks, which mainly include the distributed model [10,11] and the centralized model [12]. Among them, the distributed association scheme is easy to deploy and has low loss, and the user terminal nodes in this scheme allow users to select themselves (to the AP access point) by personal preferences and other factors. The centralized association scheme, on the other hand, uses a centralized controller (AC) to further determine the association method between APs and users in the network when aggregating the global information of the network to complete the association task [12]. The centralized association scheme is usually better able to accomplish the optimization of the system, which is the reason for the relative popularity of the centralized association scheme. The collaborative 360-degree video streaming from node-related AC scheduling to VR clients is a new topic. Closely related areas include multi-camera sensing for multi-view systems [13], immersive remote collaboration [14,15], and multi-view video coding/communication [16,17]. Existing work includes [18] base station caching, which jointly considers the backpack problem of evaluating the content popularity of base stations and minimizing the total content retrieval latency [19]. Shanmugam et al. consider the use of caching in relay nodes, which are small base stations with high storage capacity and low coverage, to reduce the latency of content delivery and to distinguish available assistants that are based on their proximity to the serving nodes [20]. Association, matching, pairing, etc., are fundamental problems in communication networks. The association between APs and VR users in this paper is in principle similar to the problem of the pairing of NOMA users and subcarriers/beam groups [21].

3. System Model

3.1. Scenario Description

This section mainly considers the scenario of the AP deployment at the edge of the network, through the VR user viewing behavior awareness characteristics, based on the characteristics of VR user behavior attributes during the viewing process, to alleviate the challenges of users in the AP association process on the network latency. According to the above scenario, we designed the network architecture as shown in Figure 1, the 360-degree video clips requested by users were delivered by the VR video server to the backbone central network, and distributed to the corresponding APs by the AC, according to the current AP association status and by the AC platform decision, and finally distributed to the VR users corresponding to the APs.

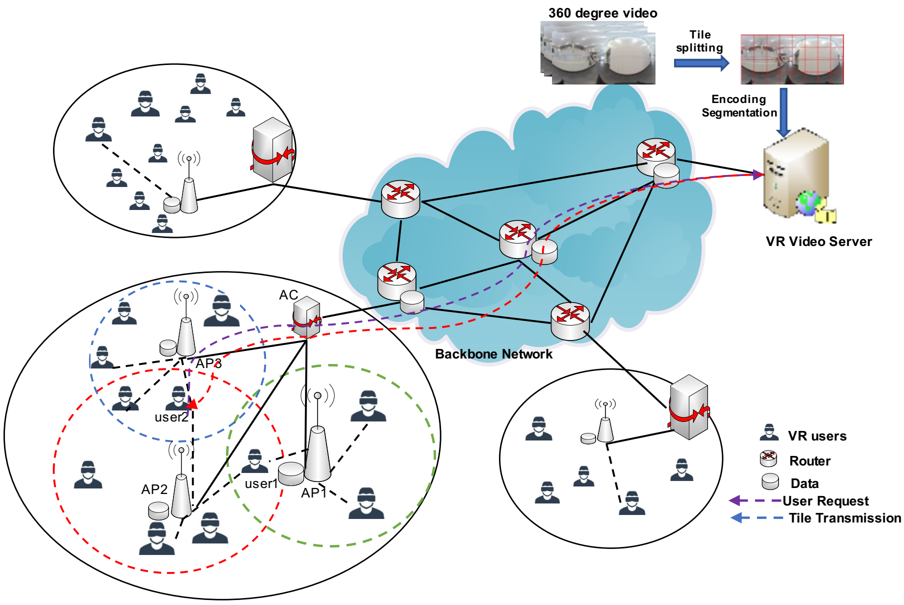

Figure 1. Edge network dense AP deployment scenario diagram.

Here, we consider the current VR 360-degree video source based on tile real-time encoding; the current AC policy module can obtain the AP bandwidth status, while the user-behavior characteristics can be sensed based on the feedback from the user's viewing behavior habits. AC can record the trajectory of the user's viewpoint after the user has watched for a period of time, based on the historical motion trajectory of the user's viewing behavior for rapid prediction, the prediction of the perceived At the same time, according to the actual usage of VR service, the user's VR device only moves in a very small range under multi-AP coverage, so we ignore the consideration of user mobility here.

The edge network architecture is shown in Figure 2 and consists of an AC, densely deployed APs, and a large number of VR user devices. In order to achieve more intelligent VR user behavior awareness, the current AC can accumulate a large amount of user viewing behavior data and user request data, as well as a certain amount of computing power and storage capacity, which can realize the allocation of resources among APs and customize the decision of user-associated APs within a certain period. At the same time, in order to ensure the convenience of VR users to access the network, APs are deployed in large numbers at the edge of the network and have a certain caching capacity, which will generate a large number of duplicate coverage areas, generating the need for VR users to select the appropriate one from multiple alternative APs to associate to access the network. We do not consider the problem of channel interference in this section for the time being.

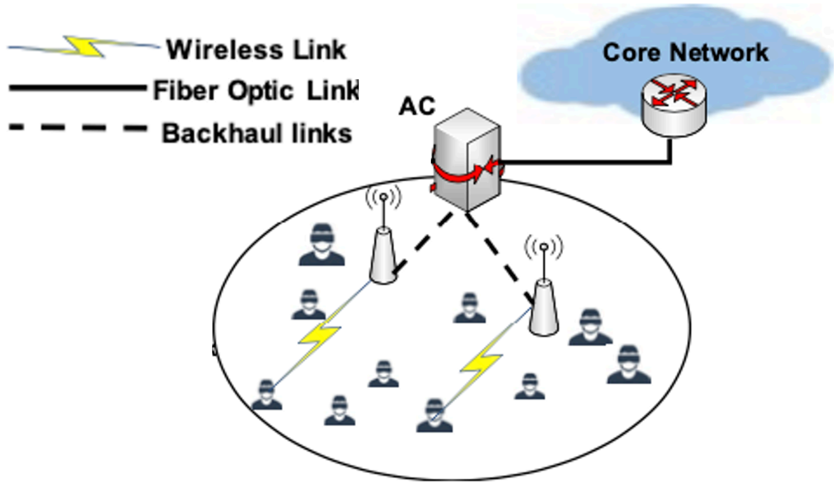

Figure 2. Edge Network Architecture.

3.2. Impact of VR User Behavior Perception on AP Association

Virtual reality users typically have a better viewing experience with head-mounted display (HMD) devices compared to regular users with smartphones. Broeck et al. analyzed the viewing experience of HMD devices, tablets, and smartphones and found that VR users had more immersive video experiences with the mobile viewport compared to the static viewport video viewed by regular users [22]. The analysis of the viewing behaviors of ordinary users tends to stay at the level of viewing content categories, while the behavioral analysis of VR users is focused on identifying more specific and representative user characteristics in navigation behavior, such as the similarity of user viewing behavior based on trajectory data. Thus, VR users are different from ordinary users and require more exploratory actions in order to secure their needs related to immersion and engagement.

At the same time, it makes sense to consider the impact of VR users' viewing behaviors on AP association to improve the overall quality of VR services. For VR users, in order to circumvent excess resource waste and save bandwidth as much as possible, only the tile in the current stage of the FoV is given to the user, not all of the tiles of the complete VR video; such methods save bandwidth, and the user FoV changes many times, leading to incremental consumption of bandwidth resources. In addition, study [4] shows that when the user's FoV is frequently adjusted, a black screen occurs, which seriously affects the user's viewing experience. Research [9] shows that in VR services that are available now, the change in bandwidth demand due to changes in viewing behavior such as head movement during viewing is much higher than the bandwidth demand generated in a calm state. Therefore, the perception of user viewing behavior is crucial to the impact of VR service quality.

In the access network scenario, users are associated with multiple access options in a multi-AP scenario, and the traditional AP association strategy usually selects APs according to signal strength. When faced with a large number of VR users, the traditional access method based on signal strength is bound to bring access overload to APs in network hotspots due to the huge bandwidth demand, which has a huge impact on VR service quality, as shown in Figure 3a. The AP has a certain caching function for the content viewed by users within a certain period of time. User download latency mainly consists of wireless transmission latency and backhaul latency (including the core network part) Users obtain content directly from the associated APs without experiencing backhaul latency, so when APs are deployed densely, excessive backhaul latency can affect the overall average download latency. As shown in Figure 3b, the current VR user User3 chooses to associate with AP2 in order to guarantee a more convenient association strategy designed based on traditional association methods that rely on load balancing and fairness to improve network performance. Here we set the AP to have a certain cache function for the content watched by the user within a certain time period. Although this improvement is helpful to reduce user backhaul latency, the current failure to consider the viewing behavior of VR users to accurately and quickly obtain the needed video resources from the corresponding AP's short-term will result in still requesting the desired resources from the AC and video server, which may have a huge impact on VR service quality. In Figure 3c for the special needs of low latency and high bandwidth faced by VR video in the AP dense deployment scenario. The current access to the VR user's viewing behavior situation is considered through the VR user's viewing behavior habits by the recent viewing behavior habits analysis, which can be obtained in the AP1 cache, and has the data required by user3. As the stored data have certain integrity, we believe that the data needed in the next phase are likely to still exist within this AP. The association with AP1 will be selected in the next association adjustment cycle and the user will only have to consider the delay in the link state in the next phase. The resulting average download delay will be much smaller than the average download delay without considering the user behavior state, thus safeguarding the VR service quality.

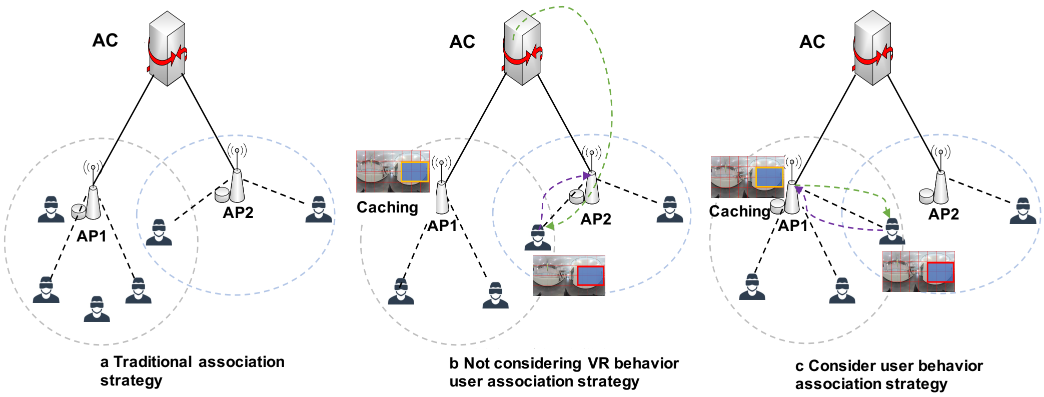

Figure 3. Impact of VR on user and AP association.

3.3. Multi-Rate and Load Balancing Analysis

In the previous subsection, we analyzed in detail the impact of our caching strategy and the perceived need to obtain the content in advance based on VR user behavior on AP association, due to the variation in signal strength, the length of the reception distance, and the signal attenuation caused by the blocking of environmental factors, such as buildings or trees in the actual scenario, combined with dense AP deployment. As a result, the transmission rate between each AP relative to the user is not the same. As shown in Figure 4, the distance between the user and the AP determines the strength of the signal they will receive under certain conditions of transmitting power and signal interference, so it can be seen that the distance between the AP and the user will be a key factor in determining the user's download delay.

An $n \times m$ dimensional rate matrix R_s is used to quantify this relationship, as shown in Equation (1).

$$R_s = \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & r_{ij} & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix} \tag{1}$$

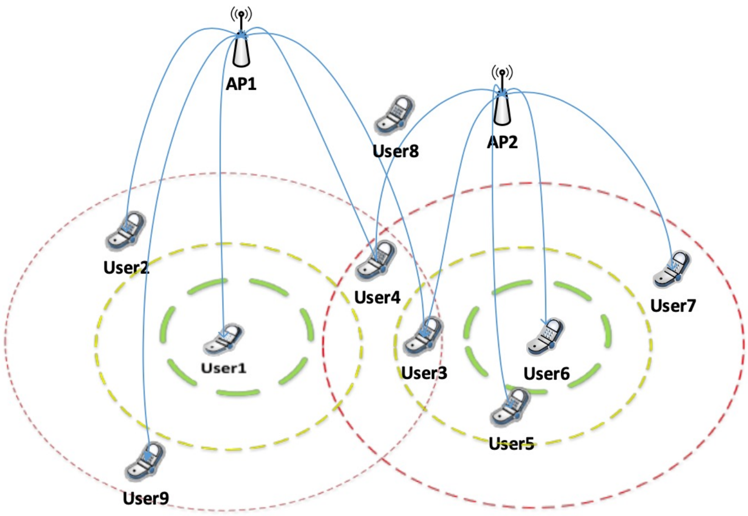

Figure 4. Different signal strengths divide the coverage area.

For the rate matrix, R_s we can consider the corresponding rate case when there are n APs and m users. The traditional association method usually refers only to the signal strength for AP association and may lead to the overloading of APs in a certain area. At the same time, multiple users associated with the same AP can lead to a significant reduction in the bandwidth resources allocated to the users, which has an impact on the current network performance. For the rate r_{ij} between user j and the associated APi in the current rate matrix R_s, we use Equation (2) to express.

$$r_{ij} = \frac{w_i}{M}\,\mathrm{d}, r_{ij} \in R_s \tag{2}$$

where w_i denotes the current bandwidth size available for APi to allocate. m denotes the number of all users currently associated with APi. We also introduce a non-fixed value parameter d greater than 0 and less than 1 to indicate the impact of environmental factors such as current signal strength on the transmission rate. Regarding the user load under AP, the average user load value of APi at a certain historical period stage can be obtained from the historical data in AC, and we $\bar{M}_i$ to represent the average user load.

4. Problem Modeling

4.1. VR User Download Latency Model

We use A_{ij} to denote the association relationship between APi and user j. If the user is associated with AP, then A_{ij} is 1, otherwise, A_{ij} is 0, and $A_{ij} \in \{0, 1\}$. where the association matrix can be represented by A.

$$A = \{A_{ij} : i \in I, j \in J\} \tag{3}$$

B_{ijk} is used to denote the presence of cached content k in AP access point i required for the current behavior-aware prediction based on user j. If B_{ijk} = 1 is cached, otherwise, B_{ijk} = 0 and $B_{ijk} \in \{0, 1\}$. The cache B matrix can be expressed as.

$$B = \left\{B_{ijk} : i \in I, j \in J, k \in K\right\} \tag{4}$$

Use E_{jk} to denote whether the current content k is requested by user j. If content k is requested by user j then E_{jk} = 1, otherwise E_{jk} = 0 and $E_{jk} \in \{0, 1\}$. The request matrix E can be expressed as follows:

$$E = \left\{E_{jk} : j \in J, k \in K\right\} \tag{5}$$

We consider that the user's download delay is mainly determined by the delay of the link between the user and the AP, and the backhaul delay. In the previous section, the transmission rate corresponding to AP i and user j is r_{ij}. Assume that when we request the viewport each time we can use the coding technique to divide the different contents into block files of the same size, and here we assume that all files are of the same size T. Among them, use r_{ij} to denote the signal-to-noise ratio of APi and user j, where the transmit power of APi is P_i, the corresponding channel The gain is f_{ij} and the noise power is σ^2. According to the signal to interference & noise ratio (SINR) formula, r_{ij} can be obtained as shown in Equation (6).

$$\gamma_{ij} = \frac{P_i f_{ij}}{\sigma^2} \tag{6}$$

Thus, for the data of the same size T to be transmitted between user j and APi, the link transmission delay Dt_{ij} is shown in Equation (7).

$$Dt_{ij} = \frac{T}{r_{ij}\log_2(1+\gamma_{ij})} \tag{7}$$

Since the data block T size is generally constant, it is evident that the transmission delay of the link is mainly determined by the transmission rate r_{ij} and the signal-to-noise ratio. For the backhaul delay, which is related to the average link distance and the load level of the AP under the current AC, we are inspired by the study [23] and set the backhaul delay as a random variable and the variable conforms to the exponential distribution while the average value is D_B. When the E_{jk} state is 1, it means that the requested content can be obtained directly from the AP currently associated with the required. The content of the request can be obtained directly from the currently associated AP without considering the impact of backhaul delay. Otherwise, the impact of backhaul delay is required. We believe that the accuracy of the prediction of user viewing behavior will directly affect the average download delay of users, and whether to consider backhaul delay can be expressed by Equation (8).

$$Db_{ij} = \left(1 - E_{jk}\right)D_B \tag{8}$$

Ultimately, the download delay resulting from downloading a content block k of size T in the state of association of user j with APi, denoted by $D^k_{i,j}$, is represented by Equation (9).

$$D^k_{i,j} = Dt_{ij} + Db_{ij} = \frac{T}{r_{ij}\log_2(1+\gamma_{ij})} + \left(1 - E_{jk}\right)D_B \tag{9}$$

Thus we can obtain the average system download delay $\bar{D}$ for n users, as shown in Equation (10).

$$\bar{D} = \frac{1}{n}\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} E_{jk}A_{ij}D^k_{i,j} \tag{10}$$

4.2. Optimization Problems

This section focuses on the joint optimization of the problem of user behavior perception associated with APs in a dense AP deployment environment. By analyzing the user viewing behavior habits to obtain the content of viewport information that users are likely to watch in the next phase, and under the constraints of the AP multi-rate and load balancing, we take minimizing the average user download delay as the optimization purpose, so as to optimize the network performance. Based on the multi-dimensional multiple-choice knapsack model MMKP (multi-dimensional multiple-choice knapsack problem) the problem model is abstracted into a generalized multi-dimensional multiple-choice knapsack (GMMKP) model, for the multi-dimensional multiple-choice knapsack problem can usually be considered as having m load-bearing weights respectively $w_k(k = 1, 2, \cdots, m)$, and j classes of $l_i(i = 1, 2, \cdots, i)$ items and the value of the i-th item of the j-th class is denoted by v_{ij}. Each backpack has a different quality constraint W_{ijk} for different items. The problem requires that only one item of the same kind can be selected to be loaded into the backpack to maximize the value of the loaded items under the limited capacity of the backpack. In the GMMKP model, we analogize the AP to a backpack, and since the cache and bandwidth resources of the actual AP are limited, they are defined as constraints of the model, for which the capacity of the AP to associate with the user can be defined as the load capacity of the backpack. For the user is analogous to different classes of items, the content requested by the user is defined as different specifications of the same kind of items, and we can consider the user's download delay for the current content as the value of the current item. Thus the problem can be abstracted as the problem of optimizing the latency of the user requesting the required content through the associated APs within the compliance constraints. Unlike the MMKP model, the current model considers that APs can be associated with all users at the moment and users can request all the content they need. The optimization objective is to minimize the average download delay of users, and the optimization model equation is shown as follows.

$$\min_{A,B} \bar{D} \tag{11}$$

Subject to:

$$\sum_{k \in C} B_{ik} \leq S, \forall i \in I \tag{12}$$

$$\sum_{i \in H(j)} A_{ij} = 1, \forall j \in J \tag{13}$$

$$\sum_{j \in N} A_{ij} \leq M_{\max}, \forall i \in I \tag{14}$$

$$B_{ijk} \in \{0,1\}, \forall i \in I, k \in K, j \in J \tag{15}$$

$$E_{ij} \in \{0,1\}, \forall i \in I, j \in J \tag{16}$$

where Equation (11) represents the minimization of the average user delay as the main optimization objective. Equations (12)–(16) present the main constraints under this optimization. The constraint of Equation (12) represents that the current AP cache content is not larger than S. The constraint of Equation (13) represents that each user can only be associated with AP in the actual state. The constraint of Equation (14) represents that the maximum number of users that can be associated with each AP is $M_{\max}$. Equations (15) and (16) represent that B_{ijk} and E_{ij} are two binary variables.

5. AP Association Model Based on User Perception

5.1. User Behavior Awareness Model

It is known from the current state of research on related work that for VR video streaming mainly uses a tile-based streaming method, in order to guarantee VR users can obtain high-quality VR video at the current moment, which needs to overcome the current mainstream HMD's refresh rate from the user's point of view needs to be higher than 75 Hz or more, while the motion to imaging (motion to photons, MTP) time delay is lower than 20 ms (MTP latency is the time from head movement to the display of the corresponding screen). To ensure the best possible quality of VR services, which requires maximum network bandwidth savings, most studies have focused on predicting user habits to maintain larger cache storage in advance to cache subsequent video content in advance to improve the smoothness of the viewing experience. However, most of the existing methods for perceiving user behavior only focus on prediction based on the synchronization trajectory of viewing points and have the problem that the prediction accuracy decreases as time continues. This section focuses on proposing newly defined parameters for perceiving user behavior.

As seen by the k-nearest neighbor classification (K-nearest neighbor, KNN) method used in the study [24], the correction regarding the value of the motion-based prediction is made with reference to the viewpoints of the N other users who are closest to the motion-based predicted viewpoints, while neglecting to consider that similar behaviors will exist between users. Thus, if the user's behavior is pre-projected, the user's behavior is very different from the N users (theoretically, each person is special, then each user produces a different VR video viewing behavior), and based on this situation, then using the nearest N users' viewpoints as a reference and thus correcting the motion-based prediction results will cause greater bias in the predicted conclusion values. Some studies [25] have shown that some of the viewing behaviors of different users in a virtual environment are similar when watching the same VR video. From the above analysis, it can be seen that for the perception of the view block and the user's viewing behavior, we then use the user's video viewing behavior habits within a certain time window as a reference. Figure 5 shows the characteristics of users' viewing behaviors. The prediction of users' viewpoint behavior is based on the historical trajectory of users' viewing behavior, and then the prediction of users' viewpoint is modified based on the similarity of movement among users. The following is the detailed methodology.

- First, the ratio of the number of tiles in the same viewpoint of the user at successive moments in a certain time period and the number of tiles in the viewpoints they generate in successive moments, respectively, is expressed in Equation (17).

$$\mathrm{Sim}_j\{t_\delta, t_{\delta+1}\} = \frac{\Omega_v\{t_\delta, t_{\delta+1}\}}{\Theta_v\{t_\delta\} + \Theta_v\{t_{\delta+1}\} - \Omega_v\{t_\delta, t_{\delta+1}\}} \tag{17}$$

- Second, δ is used to represent the sampling index $\delta \in K$ of the user's viewpoint, t_δ represents the time of viewpoint sampling, and$\Omega_v\{t_\delta, t_{\delta+1}\}$ and $\Theta_v\{t_\delta\}$ at moments t_δ and $t_{\delta+1}$ represent the number of tiles in the same user v viewpoint and the number of tiles in the user v viewpoint, respectively;
- Finally, based on the similarity of user j's viewing behavior within a time window, we introduce the concept of "mobility" of user viewing behavior, and we consider the degree of change in the user's viewing behavior within a smooth window of time to determine how many blocks of view users need to cache. This is shown in Equation (18).

$$\mathrm{Mov}_j = \sum_{\delta=0}^{D} \{1 - \mathrm{Sim}\{t_\delta, t_{\delta+1}\}\} \tag{18}$$

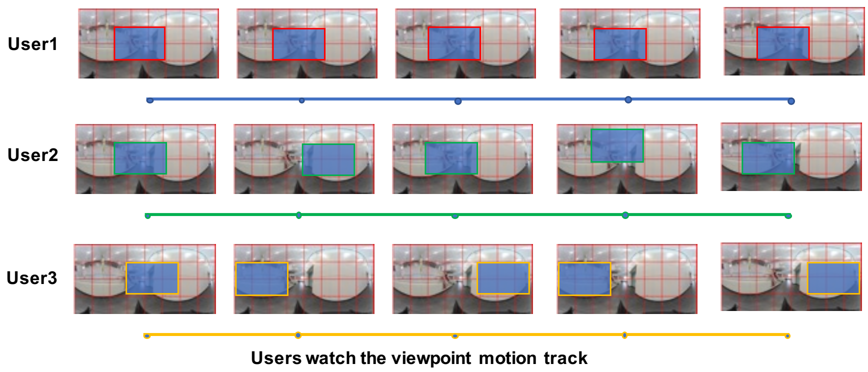

Figure 5. User viewpoint diagram.

As in Figure 5, if the time window is set to 5 seconds, the viewport of user 1 has not changed, then $\mathrm{Mov}_1 = 0$, indicating that the user's behavior when watching VR 360-degree video is relatively single, and it is more likely to choose a fixed viewport for viewing in the next moment, so the number of tiles needed for caching can meet the basic viewport. Compared with user 1, user 3's viewing behavior varies more, so $\mathrm{Mov}_3 = 4$, which indicates that users are used to choose multiple viewpoints in the process of viewing, so they need to cache the number of tiles from different viewpoints to ensure their viewing quality. Assuming that the VR content server can record the viewing behavior habits of all VR users associated with the current AP, a similar strategy to that used in the study [25] is used to assess the "mobility" characteristics of users' viewing behavior based on their initial viewing behavior based on the similarity of viewing behavior among VR users. Based on the characteristics of VR users' viewing behaviors, we use the characteristics of the collected users' "mobility" data to perform a dynamic perception of VR users' behaviors with temporal correlation, and then provide a decision basis for the AP association strategy of the edge network. The relevance of the "mobility" characteristic of VR users' viewing behavior is considered.

The data generated by VR user viewing behavior in t time units can be viewed as a series of temporal data, and the data generated in VR user-behavior habits with similar attributes on a dynamic sequence of sliding windows often also have some correlation. $\mathrm{D}_{i\,\mathrm{Mov}_{jt}}$ represents the t time windows associated with APi, and the data matrix of VR user-behavior habits collected in Equation (19) is expressed as follows:

$$\mathrm{D}_{i\,\mathrm{Mov}_{jt}} = \begin{bmatrix} \mathrm{Mov}_{11} & \mathrm{Mov}_{21} & \cdots & \mathrm{Mov}_{j1} \\ \mathrm{Mov}_{12} & \mathrm{Mov}_{22} & \cdots & \mathrm{Mov}_{j2} \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{Mov}_{1t} & \mathrm{Mov}_{2t} & \cdots & \mathrm{Mov}_{jt} \end{bmatrix} \tag{19}$$

In Equation (19), Mov_{jt} denotes the parameters collected by VR user j at time point t regarding user mobility attributes, i.e., the rows in the matrix represent the behavioral habit data of different users at the same moment, and the columns represent the behavioral habit data of the same user at different moments. The collected user data set can be considered as a variable that changes with the collection moment t. In order to analyze the correlation degree between each user and user, this paper uses the Pearson correlation coefficient (the degree of the linear correlation between two data sets) to calculate the correlation coefficient between user u and user j as shown in Equation (19).

$$rel_{uj} = \frac{\sum_{k=1}^{n}(x_{uk} - x_u)\left(x_{jk} - x_j\right)}{\sqrt{\sum_{k=1}^{n}(x_{uk} - x_u)^2}\sqrt{\sum_{k=1}^{n}\left(x_{jk} - x_j\right)^2}} j = 1, 2, \cdots, n \tag{20}$$

In Equation (20), x_{uk}, x_{jk} denote the measurement values of VR user u and VR user j at moment k, respectively, and x_u, x_j denote the measurement averages of VR user u and VR user j, respectively. The correlation coefficients take values in the range of $-1 \leq rel_{uj} \leq 1$, and the cases taking positive and negative values indicate positive and negative correlations, respectively. If users u, j are the same kind of users, then rel_{uj} indicates the correlation of similar VR users' behavioral data; conversely, if u, j are the same kind of users, then rel_{uj} indicates the correlation of dissimilar data. According to previous experimental experience, when $rel_{uj} < 0.7$, the data between VR user behavior attributes are strongly correlated, and when $rel_{uj} < 0.3$, they are weakly correlated, otherwise they are moderately correlated. N users with a strong correlation with the predicted VR users' viewing behavior during the same video were selected to calibrate the predicted VR users' viewpoints.

The plan is to do a prediction based on motion trajectory and use the combined weight voting mechanism of N user viewpoints with the highest similarity of viewing behavior habits, where the voting t of the tile can be represented by Equation (21), where ξ_{lr} represents the weight of predicted viewpoints based on the linear regression method, and ξ_{sim} represents the weight of similar user viewpoints based on linear regression method. The coverage of viewpoints under a vector of T dimensions is represented by $F(0)$, where T is the index of the tile in the raster scanning order. When the tile is in the viewpoint range, then $F(0) = 1$, and conversely, if the tile is not in the viewpoint range, then $F(0) = 0$, where the nth most similar user viewpoint is represented by O_{sim}^{n}.

$$\sigma_{t_i} = \xi_{lr} \cdot F_t(O_{lr}) + \sum_{1}^{N} \xi_{sim} \cdot F_t\left(O_{sim}^{k}\right) \tag{21}$$

Because the accuracy of the linear regression prediction method based on historical trajectories decreases gradually with time, the weights ξ_{lr} of the linear regression method are inversely proportional to time, in the form of Equation (22). In addition, let ξ_{sim} be a fixed value of 1. Using Equation (23), the weighted voting value for a specific tile can be calculated.

$$\xi_{lr} = 1/\Gamma \tag{22}$$

Finally, the voting values obtained for each tile with the weighting-based voting mechanisms are made uniform, and thus the probability of the video content k viewpoints requested by user j to fall in the tile at moment t is represented by the matrix E_{jk_t}.

$$p_i = \frac{\sigma_{t_i}}{\sum_{i=1}^{N} \sigma_{t_i}} \tag{23}$$

$$E_{jk_t} = \left\{ E_{jk} = p_i : k \in K, j \in J \right\} \tag{24}$$

5.2. User Behavior-Aware AP Association Matching Algorithm

In this section, in order to improve the network quality of VR services, we optimize the association relationship between current users and APs. In this section, we propose an AP association matching algorithm based on user behavior awareness. According to the changes of VR users' viewing behavior and the volatility of the network caused by frequent mobility of users in a dense AP environment, the static AP association method is no longer suitable for the current network environment, and a dynamic association method needs to be constructed to adjust the current association method. Therefore, we plan to dynamically update the AP association with a fixed time period to adapt to the network changes in this dense AP environment. From the impact of VR user behavior on AP association and the impact of multi-rate and load balancing in Section 3.3 of this section, we know that the users in the traditional AP association method usually decide whether to associate to the AP with the strongest signal based on the strength of the associated signal, which will lead to AP overload in dense areas, but if only load balancing is considered for association, it will have an impact on the network latency. In order to better guarantee the quality of VR services, the association strategy in this section further considers the special characteristics of VR video services, senses the behavioral actions of VR users in advance, anticipates the possible view blocks requested by users in advance, and solves the problem using the GMMKP model proposed in this Section 4.2 to reduce the transmission delay of users. For each user it is necessary to calculate the delay of the requested content after its association to each AP, and at the same time determine whether the current AP is a full load state, if the current AP does not reach the full load state and the request delay is the shortest, then associate with it, otherwise exclude this AP and choose again, complete the current association of all users with the AP, and calculate the average download delay $\bar{D}_h$ in the current state, in order to better guarantee the VR service quality set a maximum user average download delay$D_{\max}$ according to the demand of delay, change the user convenience order to re-execute steps 2 to 14, and update the user average download delay $\bar{D}_n$. Find a download delay smaller than the average download delay $\bar{D}_h$ recorded in the previous state under the premise of guaranteeing the user average delay, and thus update the record association matrix A_{ij}. Based on the VR user behavior-aware AP association algorithm requests content in one scheduling cycle time. As shown in Algorithm 1.

The input variables of the algorithm are $\left\{E_{11},\ldots,E_{jk}\right\}$ denoting the probability matrix of user j requesting video content k viewpoints falling on the tile, $\{r_{11},\ldots,r_{ij}\}$ denoting the rate matrix between user j and APi, $\left\{\boldsymbol{B}_{111},\ldots,\boldsymbol{B}_{ijk}\right\}$ denoting the presence or absence of cache content k in AP access point i required for the current behavior-aware prediction based on user j. The output variable $\{A_{11},\ldots,A_{ij}\}$ denotes the association relationship matrix between APi and user j. The algorithm has AC executed by cycle T and the longest time does not exceed $D_{\max}$. Minimizing the average user download delay is achieved as the objective based on the consideration of load balancing, and the association of user APs is performed under the guarantee of minimum user download delay and AP load balancing.

Algorithm 1 AP association algorithm for VR user behavior awareness

Input: $\left\{B_{111},\ldots,B_{ijk}\right\},\{r_{11},\ldots,r_{ij}\},\left\{E_{11},\ldots,E_{jk}\right\}$
Output: $\{A_{11},\ldots,A_{ij}\}$

```
1:  Initialisation, D_max, D̄_n, D̄_h, M_max = max, D̄_t = max, ∀i ∈ 1...i, j ∈ 1...j
2:  for user j do do
3:      Obtain the content k that user j wants to request based on the matrix E_jk;
4:      for AP i do
5:          if User j is within the coverage area of the AP i then
6:              Matrix B and Equation (10) calculate the download delay D;
7:              if D̄_n ≤ D̄_h then
8:                  D̄_t = D,record the current APi;
9:              end if
10:         end if
11:     end for
12:     A_ij = 1, M_i ++
13: end for
14: Get the current A_ij and the average download delay D̄_h;
15: while D ≤ D_max do
16:     Repeat step 14, change the order of traversing users, and calculate the new average
        download delay D̄_n;
17:     if D̄_n ≤ D̄_h then
18:         Update A_ij and D̄_h;
19:     end if
20: end while
```

6. Experimental Analysis

6.1. Simulation Settings

In this section, the numerical simulation software is used to further validate and analyze the algorithm. We construct simulation experiments based on the network scenario described in Section 3.1 and build the network topology by parameter settings. In order to verify the comparison of user behavior-aware AP association algorithm and user load balancing proposed in this paper, the current algorithm performance is analyzed based on the average delay comparison, user behavior-aware comparison and AP load of each algorithm. This section first constructs a regular area with a dense local deployment of APs and a large number of randomly and uniformly distributed users under a certain AC, as shown in Figure 6.

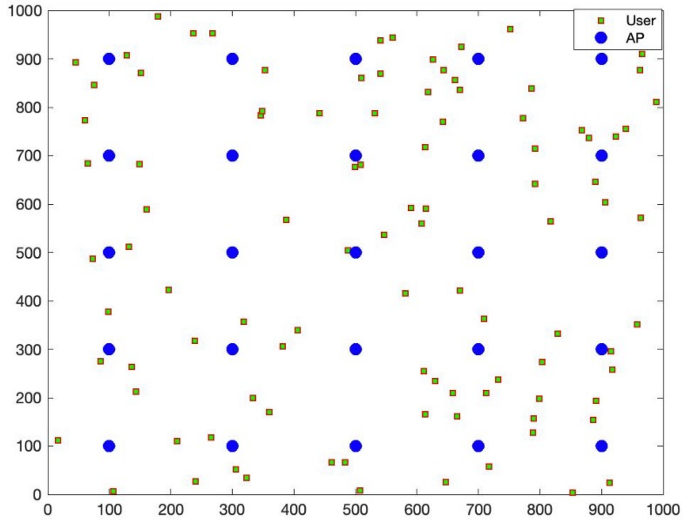

Figure 6. Network topology diagram.

The area set in this section is a square area with a side length of 10 m. Assuming that 200 users are randomly and uniformly distributed in the area, we set up 25 AP access points in the area to ensure that the area can be fully covered in order to guarantee that users can access the corresponding AP effectively. The use of frequency orthogonal channels between each AP can ignore the interference problem of neighboring frequencies, and APs with the same frequency are far apart, which can also ignore the problem of mutual interference, ensuring that each AP has to serve different users, and most users are distributed in the overlapping area between neighboring APs, so the performance of the whole network is influenced by the association relationship between APs and this part of users, which provides a basis for designing more complex and intelligent association strategies This lays the foundation for designing more complex and intelligent association policies.

In order to avoid the impact of special cases on the network, the location of users is set to be uniformly distributed. In the initial stage of the system, the AC will request video content based on the probability that the viewpoint k of user j falls on the tile, where the video content comes from the user's short-term cache, and the selected content is cached in each AP. The AC then executes the association algorithm of the AP, and the longest $D_{\max}$ is set to 15 ms, so that the association matrix A_{ij} of the user is obtained, and the relationship between the user and the AP is established and data transmission is completed. The algorithm executes multiple scheduling cycles, each cycle is set to 10 s. After multiple cycles, the data are accumulated and the AC can execute the VR user behavior awareness algorithm, where the user behavior related historical data contains all APs associated with the user, the start time and duration of the associated AP, the sequence pair of viewpoint location and time, the number of requests and the request content.

6.2. Baseline Algorithm

In order to verify the superiority and effectiveness of the algorithms mentioned in the paper, we selected two classical algorithms, CUB360 [25] and Utility evaluation(UE) algorithm [26], for comparison, and the analysis was done by the AP load situation and the average download delay of users. Here, we refer to the AP association algorithm based on user behavior awareness proposed in this section as the HWAC algorithm.

CUB360 algorithm: CUB360 algorithm in the literature [25], using cross-user behavior to predict the viewport in 360-degree video adaptive streaming, for the prediction of content popularity, for the analysis of network performance, we evaluate the latency for the index and load balancing situation under this algorithm.

Utility evaluation(UE) algorithm: The utility-oriented resource allocation algorithm, which we refer to as the "utility evaluation (UE) algorithm", is used in the literature [26].

This algorithm combines the saliency weights and FoV probabilities with the channel state information of the users. The user's channel state information is determined for each user to derive the AP access point association and the rate allocation for each user. We analyze the delay and load balancing in its network scenario according to its algorithm idea.

6.3. Performance Evaluation

6.3.1. User Download Latency Analysis

This section takes minimizing the average user download latency as the optimization objective, and analyzes the impact on the average user download latency by comparing the backhaul latency under different mean values and observing the changing trend of the average user download latency under the perceived user behavior. The specific results are shown in Figure 7. As can be seen in the figure, when we ignore the effect of backhaul delay on the average delay, the current average download delay is the link delay, and the difference in the results is small and almost negligible. However, along with the backhaul delay becomes larger, the results also show a larger difference.

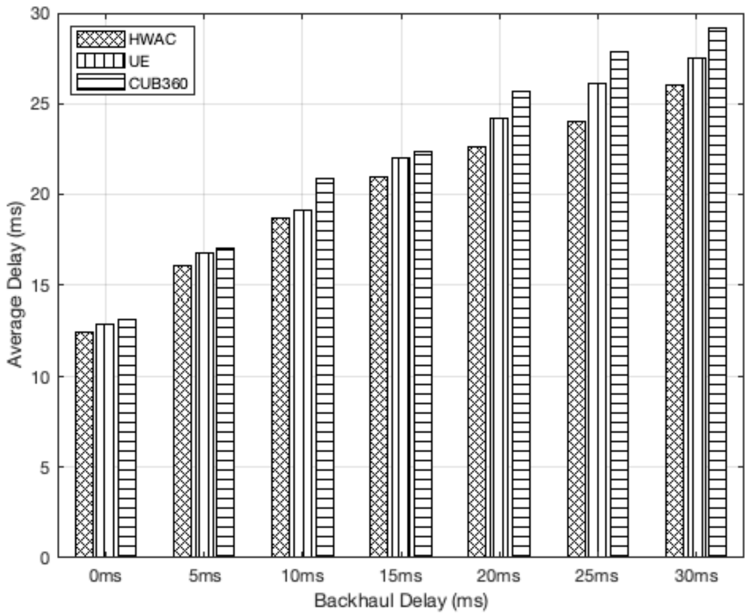

Figure 7. Average Latency Comparison.

In the association method of CUB360, although user behavior is taken into account, the impact of multi-rate and load balancing on AP association is not taken into account. The average download delays of users grow linearly with the backhaul delay. The advantage is not obvious for the backhaul link congestion and AP dense network scenario.

The impact of backhaul delay on the average download delay has been attenuated in the UE algorithm by proposing a new buffering strategy to mitigate the impact of the short-time prediction problem of transmitting 360-degree videos in time-varying networks, and the results are slightly better than those of the CUB360 algorithm. However, for a VR video user, the viewing process not only considers the user behavior, but also the influence of the viewport exists, so the buffering-only strategy ignores the time-varying nature of different user behavior features viewing behavior.

Therefore, in the HWCA algorithm, the user's viewing behavior is fully sensed and the load balancing problem is considered, and the current optimal user–AP association scheme is obtained based on the user download delay optimization, and the results are better than other optimization algorithms.

For the simulation data of the VR video source, we used the 4K resolution VR video from the dataset given in the study [27], where the number of tiles is 4 × 8. The user predicted in the simulation is randomly selected from the 48 users given in the study, and the first half of the user's viewpoint trajectory is used for the behavior prediction. The second half of the user's viewpoint trajectory is used to evaluate the performance of the user's behavior prediction. According to the HWCA algorithm proposed in this section, it relies on the accuracy of user behavior perception, and also has a strong relationship with the perception period. As seen in Figure 8, the average user latency decreases with increasing prediction accuracy, thus indicating that the behavioral perception of user viewing attributes has an impact on accuracy and VR service quality assurance.

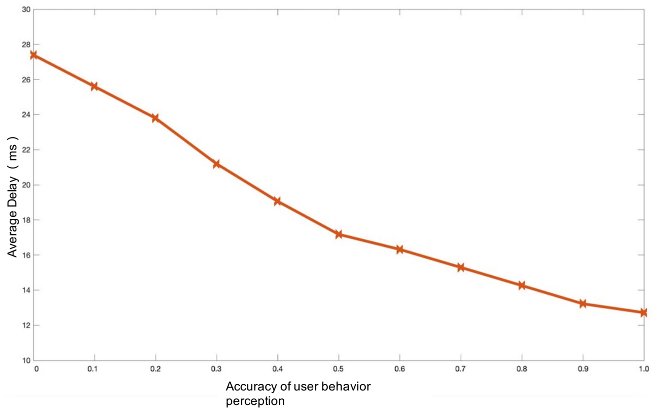

Figure 8. Comparison of user behavior perception.

6.3.2. AP Load Analysis

The AP load balancing problem at the edge of the network has always been the focus of research. There is a limit to the maximum number of associations that each AP can withstand, and the QoE of each user decreases as the number of users associated with the AP increases, which makes the performance of the whole network decrease as well. The performance of load balancing is discussed below based on three algorithms. Here we refer to the number of users associated with each AP in each cycle as the load, and the statistics of the scheduling cycle here are based on 15 APs selected arbitrarily from 25 APs and the statistics of these 15 APs.

Figure 9 shows the load of the CPUA algorithm, which does not consider the load balance of users, and there is a large difference between the maximum and minimum loads, and the number of loads of the same AP fluctuates widely from cycle to cycle, and there is also a large difference between different loads in a uniform cycle, it can be seen that aggregation of a large number of users with the same behavior leads to a large number of users being attracted to the same AP, but another portion of APs with relatively low loads. This can also have a significant impact on network performance, and the overall state of the AP load seems to be out of balance.

Figure 10 shows the AP load under the UE algorithm, fundamentally, since the UE algorithm proposes an algorithm to decide which user should connect to which Wi-Fi access point and selects the appropriate transmission rate for each tile of each video, thus maximizing the overall system utility. However, there are some problems with the early load balancing, but the UE algorithm achieves good results as the buffer has accumulated making the periodic load of the algorithm more balanced in the later stages. From the above analysis, it can be seen that the UE algorithm has limited consideration for user download latency in order to guarantee this performance. Therefore, the core index of VR quality of service cannot be well guaranteed.

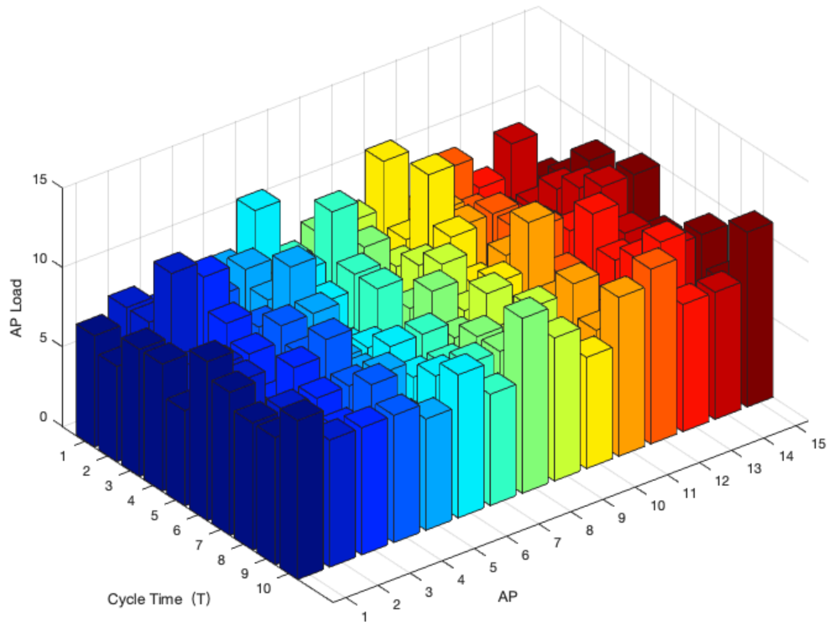

Figure 9. CUB360 algorithm for load balancing.

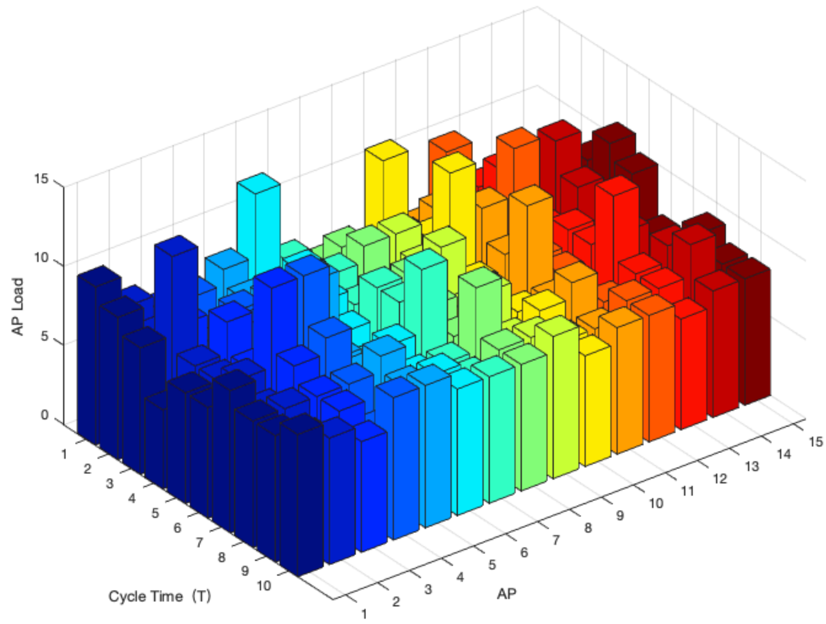

Figure 10. FAME algorithm for load balancing.

In Figure 11, the load of APs in our proposed HWCA algorithm can be seen, in which there is a pattern to follow. In the dimension of the AP load, the minimum value of each AP load is 6 and the maximum value is 10. In the 10 cycles, the load values of AP14 and AP15 are both large and the load levels between them are similar, and the load values of AP2 and AP8 are both small and the load levels between them are similar. The rest of the AP load values fluctuate around 8, and the load distribution is relatively average. Therefore, if the overall AP load is in a more balanced state, there may be an AP with a low load and an AP with a high load in each AP group, and an AP with normal load. The loads of different APs in the same cycle vary less, and the same AP does not vary much from cycle to cycle, perhaps due to the perception of user behavior caused by the correlation switching and thus the change. In general, there are no wasted AP resources and no AP overloads, and the loads of APs are relatively average.

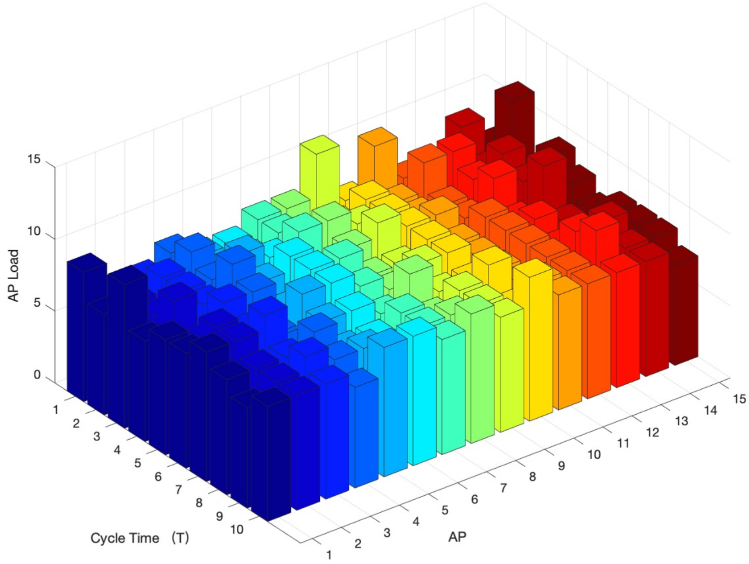

Figure 11. HWCA algorithm for load balancing.

7. Discussion

With the increasing functionality of VR services, the key aspect of VR service development is to guarantee user immersion, presence, and interactivity in order to make the immersive experience as close to the real environment as possible [28]. VR user attributes at the edge of the network based on user behavior perception through the optimization of user association strategy and thus to ensure the quality of VR video service network application research is in a relatively important position at this stage. With the rapid development of communication technology, multi-access edge computing (MEC) is considered to have a driving role in VR development. Therefore, it is a very interesting research point to study the trade-off between the need to ensure high bandwidth and low latency in VR systems and QoE optimization based on the choice of user access methods for MEC. QoE optimization of VR systems needs to consider the cost of reducing caching and computation while ensuring the user viewing experience. Balancing user QoE with the cost of caching and computing resources, with the involvement of MEC, is a future research direction.

8. Conclusions

In this paper, we propose a VR user behavior-aware AP association method. First, the edge network scenario and system model of VR service were constructed, and the impact of VR user behavior awareness on AP association was analyzed for multi-rate and load balancing. The user's viewing behavior directly affects the average download delay of the access AP, the real-time acquisition of the real user's viewing behavior was predicted, and the viewing behavior of the user end and the performance of its access AP were inextricably linked. Second, we proposed a fast user behavior awareness model; this model is based on historical data for prediction, based on the analysis of user viewing behavior states, in the case of unavailable real user viewing behaviors, to predict the probability that the viewing gaze point of different users at the edge of the network will fall in different areas of the VR video. Finally, by minimizing the average download delay of access points, the key here is to form a many-to-one generalized multidimensional multiple-choice backpack problem to solve the association problem between APs and users, and due to the high complexity of the problem, we chose the suboptimal solution in order to ensure the current network performance. The results show that the user behavior-aware AP association algorithm performs well compared to traditional algorithms in terms of both average download delay and load balancing, and can better secure VR services.

Author Contributions: This work was mainly performed by J.R., Y.W. (planning of the work, conceptualisation, investigation, methodology, data curation, formal analysis, resources, software, visualisation, and original draft preparation) and was completed with key contributions from Z.F., Y.S. and T.Y. (planning of the work, conceptualisation, supervision, validation, manuscript review and editing, and funding acquisition). All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: I would like to thank my wife (Xiaoyun Ma) and children (Dudu) for their wise advice and compassion. You have always been there for me.

Conflicts of Interest: The authors declare no conflict of interest.

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