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A Social-Energy Based Cluster Management Scheme for User-Centric Ultra-Dense Networks

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ABSTRACT With the exponential growth of traffic demand, ultra-dense networks are proposed to increase the network capacity. However, the high-density access point (AP) deployment will increase the complexity of AP coordination, and AP cluster (APC) needs to be considered in practical implementations. Due to the dynamic changes in spatiotemporal distribution of users and service demand, we propose a social-energy-based cluster management (SECM) scheme in order to reduce APC update frequency. Specifically, in social domain, we propose a congeniality-based personalized recommendation (CPR) algorithm to predict users' incoming requests. We further propose a CPR-based AP cluster algorithm to solve the matching problem among users, APs, and content. In energy domain, we propose an inter-cluster energy cooperation scheme to avoid the shutting down of members in AP cluster and reduce the update of clusters. Numerical results demonstrate that our proposed scheme can achieve a gain of 77.8 % in the APC management utility averagely, without loss of fairness compared with the other state-of-the-art schemes.

INDEX TERMS Ultra-dense network, mmWave, AP cluster, matching game, personalized recommendation.

I. INTRODUCTION

According to Cisco, aggregate smartphone traffic will be seven times greater than it is today, with a compound annual growth rate (CAGR) of 48% [1]. In order to satisfy the growing traffic demand, UDN has been proposed as a promising technique in 5G [2]. In UDN, APs are typically deployed in hot spots (e.g., airports, markets, and train stations) with low transmit power. Although UDN can substantially improve the data rate of users (e.g., up to 10 Gbps), the network densification is still limited.

Since the density of APs is much higher than that of UEs in UDN, multi-connection technology becomes critical. Coordination between APs in the network is complicated due to the synchronization requirement, additional pilot overhead, complex beamformer design, and scheduling. To reduce these overhead, small size of cooperation clusters are required. Clustering for cooperation set is key for optimizing the performance in multi-connection technology. The clustering algorithm was first proposed in a self-organizing network such as a sensor network [3]. After that, there are many studies which have considered the idea of clustering APs into coordinated groups. In [4], the authors proposed a dynamic clustering-based spectrum allocation scheme in a dense cell environment. However, the authors only considered resource allocation. In [5], the authors proposed a cooperative scheme for femtocell network. In their work, femtocells cooperate by forming coalitions which interference is eliminated among femtocells through interference alignment. However, the author assume split spectrum operation, where femtocells have their dedicated spectrum which reduces spectrum efficiency. [6] further proposed a clustering-based resource allocation and interference management scheme for femtocells based on exhaustive search.

Although those clustering methods perform well, they are too complex to be suitable for dense networks. Due to the high AP density in UDN, traditional network-centric clustering schemes are inapplicable due to the precise synchronisation requirement within coordinated cells, additional pilot overhead, additional signal processing, complex beamforming design. Thus, [7] proposed three low signalling overhead clustering algorithms in MIMO interference channels. In [8], a graph-based low complexity dynamic clustering algorithm is proposed, which dividing the whole network into a number of clusters under size constraint, the maximum intra-cluster interference and minimum inter-cluster interference in ultra dense network. But those above studies only take consideration of physical constraints like interference.

Additionally, spatiotemporal distribution of users and service demand will change dynamically. Therefore, social information also has huge potential value in clustering algorithms. Reference [9] proposed a dynamic clustering and user association scheme in wireless small cell networks with social considerations. In their work, the author decomposed the user association into a dynamic clustering problem and proposed a social similarity based user association approach to solve the problem. In [10], a service-aware user-centric clustering and scheduling scheme is proposed to improve delay and throughput performances for cloud-RAN with coordinated multi-point transmission. This approach creates overlapping clusters on a per-user basis adaptively based service demand. However, these social-aware clustering schemes only consider optimizing throughput performance without taking into account the huge complexity and energy efficiency of dense networks.

To this end, we propose a social-energy based cluster management scheme by analyzing the User-centric UDN (UUDN) architecture proposed by [11]. In the social domain, in order to predict users' incoming requests, we propose a Congeniality-based Personalized Recommendation algorithm. Particularly, predicting the incoming service request of UE can help reduce the updating frequency of AP cluster, thereby reducing the signaling overhead of the control plane. Then, we formulate the social-aware AP cluster as a 3-dimensional (3D) matching problem. To tackle the intractability of the 3D matching problem, we employ a series of approximations to simplify it and propose the CPR-based AP Clustering (CPRAC) algorithm. However, the AP's on/off will also lead to AP cluster update, thus, in energy domain, we also propose an inter-cluster energy cooperation scheme to avoid the shutting down of APs and reduce the update of cluster. Our contributions can be summarized as follows:

1) A UUDN architecture with local access and core network is proposed, where local control center includes optical CoMP function, energy cooperation function and AP cluster function, and network control center contains download history analysis function. Aggregator implement the two-way energy trading between the power grid and AP cluster.
2) We formulate the social-aware AP cluster as a 3-dimensional matching problem among AP, UE, content and propose a matching game based on the social domain to achieve AP cluster.
3) After AP cluster, a shortest path-based energy cooperation algorithm is proposed for inter-cluster energy cooperation.
4) We analyze the users' preference with the personalized recommendation by using three public datasets and propose CPR to predict users' incoming request. The Precision and Recall are much higher than traditional algorithms like Global Ranking Method (GRM) and Collaborative Filtering (CF).

The rest of this paper is organized as follows. Section II describes the system model consisting of UUDN architecture and mmWave model, then we formulate the APC management problem based on social domain and energy domain. In Section III, the clustering problem based on social domain is formulated as a matching game and the energy allocation subproblem is formulated as an intra-cluster energy cooperation. Simulation results are presented in Section IV. Finally, Section V concludes the paper.

II. SYSTEM OVERVIEW

In this section, we provide a detailed architecture of UUDN where the mode is changed from network controlling users to network serving users. In addition, we introduce a millimeter wave model using a free space line-of-sight propagation model.

A. UUDN ARCHITECTURE

In a typical UDN, refers to the networks, the density of access points is much larger than that of users, which can achieve hundred of times improvement of capacity in hot-spot areas. Therefore, UDN is promoted as one of the major technology to meet the requirements of ultra-high traffic volume density in 5G system. As one implementation of UDN, UUDN can serve users seamlessly without users' involvement through virtual cell technology [11]. In this paper, we propose an architecture of UUDN by decoupling the user plane and control plane from the radio access network (RAN) and core network (CN) side. An illustration of UUDN architecture is shown in Fig. 1.

In this architecture, there are a set $\mathcal{A} = \{1, 2, \cdots, A\}$ APs and a set $\mathcal{U} = \{1, 2, \cdots, U\}$ UEs randomly distributed within the UUDN. Assume that dense deployed APs can be organized intelligently as virtual cells to serve users in a joint manner, e.g., using CoMP, which can guarantee the QoS of each user. All kinds of APs are connected to users by mmWave access links and the Local Access by fiber fronthaul. Local Access consists of three parts, namely, Local Control Center (LCC), Local Data Center (LDC) and Aggregator. LCC is responsible for new user-centric functions, such as AP cluster, optimal CoMP and Energy Cooperation. LDC provides the user plane functions and acts as a plain access router to forward content chunks to users. The aggregator is an energy pool module that can store the renewable energy collected from APs and distribute the energy to APs. At the network side, the Network Control Center (NCC) conducts Download History Analysis function in terms of social data and Network Data Center (NDC) serves as the data gateway for content distribution.

B. MILLIMETER WAVE MODEL

Due to the intensive deployment of APs, the complex aggregation interferences have been a major challenge for UDN. Since the interference from nearby mmWave APs can be small due to shorter transmission distance and sensitive blockage effects of mmWave spectrum, APs will be essential for these spectrums [12]. Moreover, the spectrum resource is abundant so that it can support high data rate

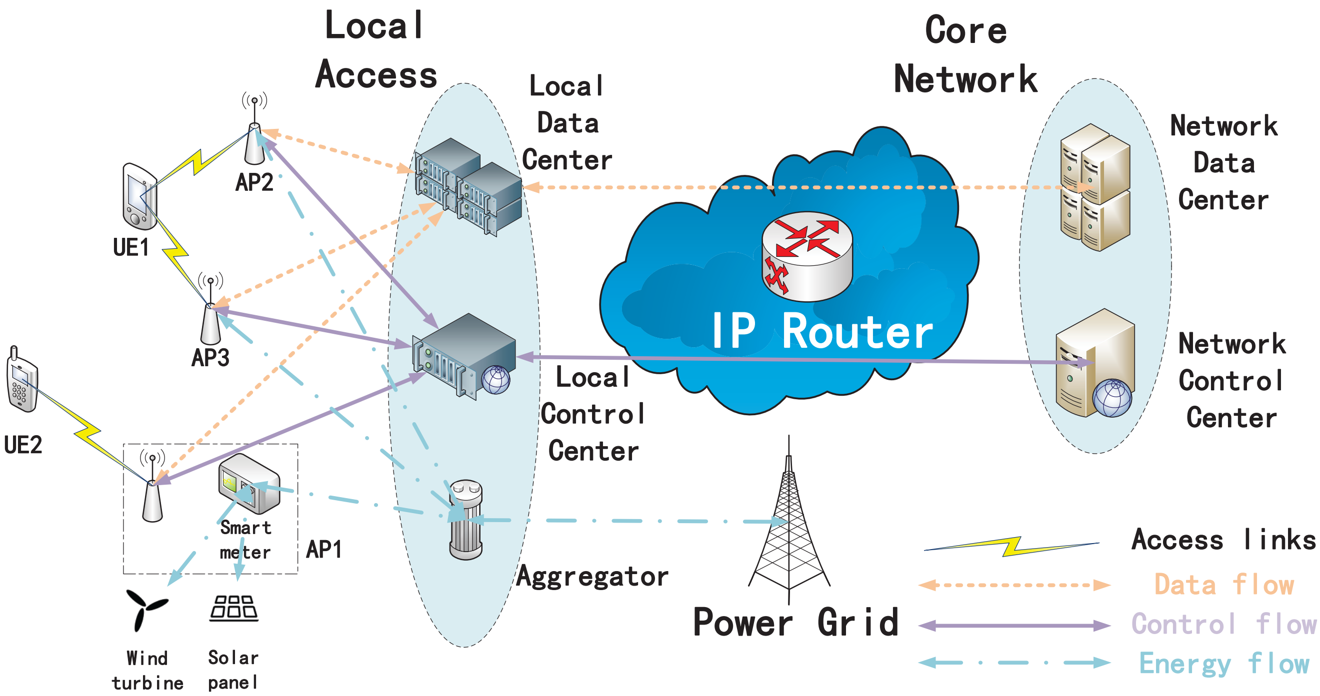


FIGURE 1. Illustration of UUDN architecture.

for communications. Therefore, a dense deployment of the the mmWave APs is required.

Due to limited coverage and dense deployment of APs, in this paper, we only consider line-of-sight (LOS) link for simplicity. In a mmWave network. The pathloss (in dB) for a LOS link with distance d can be given as [13]:

$$\mathrm{PL}_{LOS}(d) = 20\log_{10}(4\pi/\lambda) + 10\alpha_L \log_{10}(d) + \chi_{\sigma_L} \quad (1)$$

where α_L is the pathloss exponent of a LOS link, and χ_{σ_L} is LOS shadowing and $\chi_{\sigma_L} \sim \mathcal{N}(0, \sigma_L^2)$, where σ_L^2 is the variance of the Additive White Gaussian Noise (AWGN). In LOS link model, σ_L always has a small effect on the pathloss. λ is the carrier wavelength.

Due to the strong propagation loss, fast channel variation and low diffraction ability of mmWaves, directional beamforming is required in mmWave communication. For AP a, the antenna gain is a function of the steering angle θ, which can be given as [14]:

$$G_a(\theta) = \begin{cases} G_a, & \text{if } |\theta| < \theta_a \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where θ_a is the main lobe width. The interference caused by side lobe is ignored in our network.

By using the advanced multi-user interference cancellation, such as optical CoMP technology [15], Zero-forcing (ZF) precoding and the complex blockage in urban, the inter-user interference can be almost eliminated. As a result, signal-to-noise ratio (SNR) provides a good approximation to signal-to-interference-plus-noise ratio (SINR). For each time slot, the SNR between an AP $a \in \mathcal{A}$ and an UE $u \in \mathcal{U}$ can be written as:

$$\mathrm{SNR}_{ua} = \frac{P_a G_a G_u g_{au} \mathrm{PL}_{LOS}^{-1}(d_{ua})}{N_0} \quad (3)$$

where P_a is the transmission power of AP a, G_a is the antenna gain of AP a and G_u is the antenna gain of UE u. g_{au} stands for the rayleigh fading, $\mathrm{PL}_{LOS}^{-1}(d_{ua})$ is the pathloss between AP a and UE u. Noise power N_0 can be given as $BW\sigma_L^2$, where BW is the bandwidth of an AP. We assume all APs use the same bandwidth.

III. PROBLEM FORMULATION

In this section, we first formulate the AP cluster problem as a one-to-many matching problem between APs and UEs, and then transform the matching problem into an optimization problem based on social domain and energy domain.

Considering the constrained storage capacity, each AP can only cache the limited number (i.e. N_c^{max}) of contents. For analysis simplicity, we consider that the APs and the UEs are all equipped with single antennas and each AP can only serve one active UE in each time slot [16]–[18]. For each AP a, we define the content cache vector as $\mathbf{v}_a^C = (y_{a1}, y_{a2}, \cdots, y_{aC})$, where y_{ac} is binary decision variable and will be introduced later. For each user, LCC will assign a cluster of APs (with a maximum number of N_a^{max}) for serving. We assume that each user requests content at the beginning of an interval with duration time T. Once an AP cluster (APC) is established, a unique APC-ID will be assigned by NCC and stored in LCC. Then, those APs in APCs will be updated according

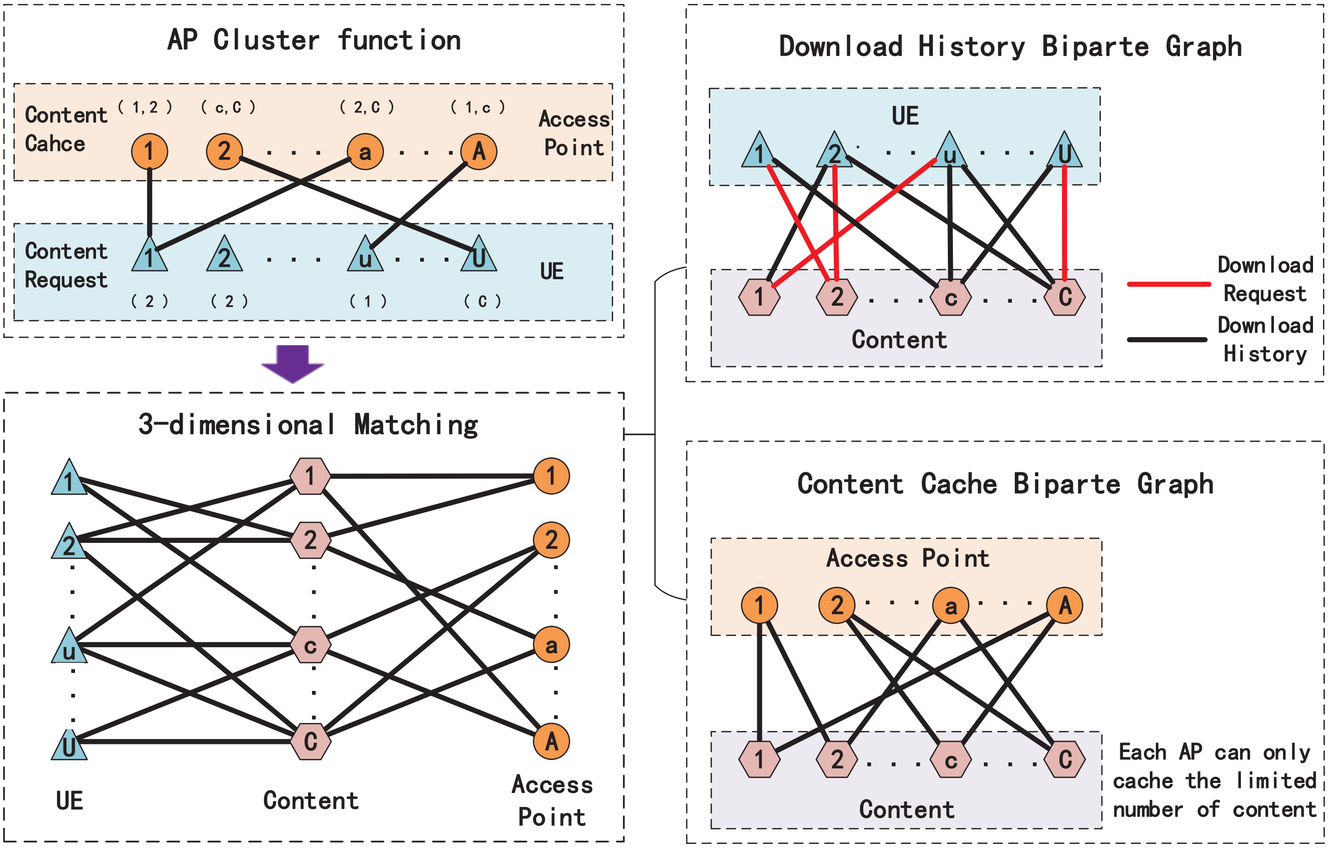


FIGURE 2. Hierarchical bi-partite graph for AP cluster function.

to updating cases. We define the following two updating events:

1) event R1: serving AP does not cache the content requested in next time interval T.
2) event R2: serving AP ends up due to insufficient energy.

Hence, we consider the APC management from the social and the energy domains, respectively.

In social domain, the user-centric AP cluster is shown in Fig. 2. In order to minimize the number of triggering event R1, we formulate the clustering problem as a 3-dimensional matching problem using social analysis.

NDC gathers content download records of all registered users and saves them as entries in databases. Then, NCC will query the entries and predict users' future requests based on Download History Analysis. Therefore, LCC can achieve the clustering more effectively by reducing the number of triggering event R1, when users request next content.

In order to predict users' incoming requests, we propose a Congeniality-based Personalized Recommendation (CPR) algorithm. In download history bi-parte graph in Fig. 2, we model users and content as nodes and use a bi-parte graph $G = (\mathcal{U} \cup \mathcal{C}, E)$, where the edges represent download history. The left vertices $\mathcal{U}$ correspond to users while the right vertices $\mathcal{C}$ correspond to the content. Except for the set of users who download the content, we ignore all other feature about content such as size, popularity, and download time of the content. The edge $e = (u, c)$ represents user u download content c. For a user u, The less the amount of content u downloads, the more important to estimate preferences for each downloaded content. With all other things being equal, for each vertex $u \in \mathcal{U}$, the fewer edges of u, the greater weight of each edge. Hence, we can use $\Gamma(u)$ to represent edge weight, where $\Gamma(u)$ is the neighborhood list of user u. For any user u_1 and u_2, if they have more common download history, the more likely they have common interests, which can be defined as *Congeniality* [19], as given by:

$$C_{u_1 u_2} = \frac{|\Gamma(u_1) \cap \Gamma(u_2)|}{|\Gamma(u_1) \cup \Gamma(u_2)|} \tag{4}$$

Furthermore, for each user u, considering both download request and download history, we denote the user's download vector as $\mathbf{v}_u^D = (z_{u_1}, z_{u_2}, \cdots, z_{uC})$, where z_{uc} is a binary decision variable, as given by:

$$z_{uc} = \begin{cases} 1, & \text{if user } u \text{ downloads the content } c \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Collaborative Filtering (CF) algorithm [20], [21] is a popular personalized recommendation algorithm. In CF, if people have similar preferences and their preferences are stable, their incoming requests can be predicted according to their past preferences. In CF algorithm, we choose cosine similarity measure method, and for any user u_1 and user u_2, the similarity between them can be written as follow:

$$S_{u_1u_2} = \frac{\sum_{c\in\mathcal{C}} z_{u_1c}z_{u_2c}}{\sqrt{\sum_{c\in\mathcal{C}} z_{u_1c}^2}\sqrt{\sum_{c\in\mathcal{C}} z_{u_2c}^2}} \tag{6}$$

Thus, with the help of congeniality, the preference of user u to content c in CPR can be calculated as:

$$P_{uc}^{CPR} = \sum_{u'\in\mathcal{U},u'\neq u} C_{uu'}S_{uu'}z_{u'c} \tag{7}$$

For each user u, we define the user's preference vector $\mathbf{v}_u^P = (P_{u1}, P_{u2}, \cdots, P_{uc}, \cdots, P_{uC})$, where P_{uc} is the preference of user u for the content c. In particular, we assume that users do not download duplicate content, that is, if a user u has already downloaded a content c, the preference $P_{uc} = 0$. In this case, the preference vector of user u can be calculated as $(1 - \mathbf{v}_u^D) \odot \mathbf{v}_u^P$, where $\odot$ is a new operator and defined as:

$$\begin{aligned}(a_1, a_2, \cdots, a_n) &\odot (b_1, b_2, \cdots, b_n)\\ &= (a_1b_1, a_2b_2, \cdots, a_nb_n)\end{aligned} \tag{8}$$

In energy domain, all APs are assumed locally deployed with solar panels and/or wind turbines for energy harvesting from the environment and equipped with smart meters to enable their energy cooperation through the aggregator in Local Access [22]. In UUDN architecture, there are thousands of APs and the harvested energy can benefit the operators. In order to decrease Operating Expense (OPEX), Local Access will decrease the amount of power it buys from the Power Grid, instead, taking advantage of the renewable energy harvested from APs through Energy Cooperation function.

Energy cooperation is a cost saving approach from the perspective of operators, where APs are allowed to employ two-way energy trading or sharing for better utilization of the energy. It is worth noting that, it is complicated for LCC to directly control thousands of APs, thus, the energy trading and sharing in Local Access should be enabled by using the aggregator [23]. We can divide APs into a finite number of clusters and aggregator can serve as control center with low complexity by implementing intra-cluster energy cooperation.

In our energy cooperation model, at the beginning of an interval τ, we assume the available energy at AP a is $E_a(\tau)$, the amount of energy harvested by AP a per unit time is E_a^{in}. The transferred energy from AP a to AP i is $\varepsilon_{ai}(\tau)$ and the energy transfer efficiency between a and i can be represented as β_{ai}. Therefore, the available energy of AP a at time τ can be written as follow:

$$\begin{aligned}E_a(\tau) = E_a(\tau-1) &+ \sum_{i=1,i\neq a}^{A} \beta_{ai}\varepsilon_{ai}(\tau-1)\\ &- \sum_{i=1,i\neq a}^{A} \varepsilon_{ia}(\tau-1) + E_a^{in}\end{aligned} \tag{9}$$

To guarantee the performance of user plane and control plane in UUDN architecture, we should consider not only SNR to ensure user experience, but also signalling overhead caused by AP updating. Hence, considering both throughput and cost, we formulate the APC management utility as the difference between the total network throughput and the overhead caused by clustering updating cases. In this paper, we assume users request a new content at a time interval T, and the overhead caused by one AP handover is $\mathcal{C}$. Thus, the utility maximization in UUDN can be formulated as:

$$\begin{aligned}
&\max_{x_{ua}} \sum_{u=1}^{U}\sum_{a=1}^{A} x_{ua}\left(BW\log_2(1+SNR_{ua}) - w_1\mathcal{C}\frac{n_a}{T}\right)\\
&s.t.\ C1: n_a = \begin{cases}0, & \text{if } y_{a\zeta_a} = 1 \text{ and } E_a \geq P_aT\\ 1, & \text{otherwise}\end{cases}\\
&\quad C2: y_{ac} = \begin{cases}1, & \text{if AP } a \text{ cache the content } c\\ 0, & \text{otherwise}\end{cases}\\
&\quad C3: x_{ua} = \begin{cases}1, & \text{if AP } a \text{ serve the UE } u\\ 0, & \text{otherwise}\end{cases}\\
&\quad C4: \sum_{c=1}^{C} y_{ac} \leq N_c^{max}\\
&\quad C5: \sum_{u=1}^{U} x_{ua} = 1\\
&\quad C6: \sum_{a=1}^{A} x_{ua} \leq N_a^{max}
\end{aligned} \tag{10}$$

where ζ_a is the content requested by user who is served by AP a. E_a is the remaining energy in AP a, P_a is the power consumption which is composed of two parts: the dynamic power consumption related to the data transmission for serving UEs, and the constant power consumption (e.g., at the circuits and air conditioners) for maintaining necessary operations. n_a is the number of handover during AP cluster updating. $C1$ ensures that both two cases can trigger the handover. $C2$ and $C3$ are binary decision variables. $C4$ imply that each AP can only cache a certain number of content because of limited storage capacity and $C5$ specifies that each AP can only serve one user at a time. $C6$ indicates that each user can only be served by limited APs due to the complexity of cooperative transmission.

The above problem is a multidimensional $0-1$ knapsack problem (MKP) [24]. Hence, the problem is an NP-hard, and it is difficult to find the optimal solution by classical optimization approaches, especially in the UDN scene. In order to quickly achieve a good performance, we decompose the optimization problem into two subproblems, i.e., AP cluster subproblem and intra-cluster energy allocation, and propose a social-energy based cluster management scheme which consists of social-aware AP cluster scheme and intra-cluster energy cooperation scheme to solve them respectively.

A summary of key notations is presented in Table 1.

TABLE 1. KEY notations used in this article.

Variables	Explanation
$\mathcal{A}$	AP set
$\mathcal{U}$	UE set
α_L	pathloss exponent
χ_{σ_L}	LOS shadowing
σ_L^2	variance of the AWGN
λ	wavelength
θ	steering angle
θ_a	main lobe width
P_a	the transmission power of AP a
G_a	the antenna gain of AP a
G_u	the antenna gain of UE u
N_0	Noise power
BW	the bandwidth of an AP
N_c^{max}	The maximum number of content an AP can cache
y_{ac}	binary decision variable whether AP a cache the content c
N_a^{max}	The maximum number of APs in a cluster
$\Gamma(u)$	the neighborhood list of user u
$C_{u_1u_2}$	Congeniality between u_1 and u_2
z_{uc}	binary decision variable whether UE u downloads the content c
$S_{u_1u_2}$	the similarity between u_1 and u_2
P_{uc}^{CPR}	the preference of user u to content c in CPR
P_{uc}	the preference of user u for the content c
$E_a(\tau)$	the available energy at AP a
E_a^{in}	the amount of energy harvested by AP a per unit time
$\varepsilon_{ai}(\tau)$	The transferred energy from AP a to AP i
β_{ai}	the energy transfer efficiency between a and i
x_{ua}	binary decision variable whether AP a serve the UE u
ζ_a	the content requested by user who is served by AP a

IV. THE SOCIAL-ENERGY BASED CLUSTER MANAGEMENT SCHEME

In this section, we resort to the SECM scheme to solve such a complicated problem. In our scheme, we use the recommendation system theory and matching game theory to solve the AP cluster subproblem. After AP cluster, we use graph theory and greedy algorithm to solve the intra-cluster energy allocation subproblem.

A. SOCIAL-AWARE AP CLUSTERING AS A MATCHING GAME

The AP cluster subproblem is similar to the college admissions, which was proposed by Gale and Shapley [25]. Therefore, we model the clustering problem as a matching game. In a matching game, each player must rank the players who are in the opposing set by using a preference relation that captures this players evaluation of the players in the opposing set.

In this paper, we formulate the AP cluster subproblem as a two-sided many-to-one matching game, where each user $u \in \mathcal{U}$ will be assigned to at most N_a^{max} AP $(a_1, a_2, \cdots, a_{N_a^{max}} \in \mathcal{A})$. Hence, we formulate the subproblem as a many-to-one matching game given by the tuple $(\mathcal{U}, \mathcal{A}, \succ_{\mathcal{U}}, \succ_{\mathcal{A}})$, where $\succ_{\mathcal{U}} = \{\succ_u\}_{u\in\mathcal{U}}$ denotes the set of preference relations of UEs and $\succ_{\mathcal{A}} = \{\succ_a\}_{a\in\mathcal{A}}$ denotes the set of preference relations of APs. Then, we define the notion of a matching as:

Definition 1: A matching μ is defined as a function from the set $\mathcal{U}\cup\mathcal{A}$ into the set of $\mathcal{U}\cup\mathcal{A}$ such that $(u \in \mathcal{U}, a \in \mathcal{A})$: 1) $\mu(a) \in \mathcal{U}$ and $|\mu(a)| = 1$ for each AP, 2) $\mu(u) \in \mathcal{A}$ and $|\mu(u)| \in (1, 2, \cdots, N_a^{max})$ for each user and 3) $a \in \mu(u)$ if and only if $\mu(a) = u$.

To fully describe the matching μ, we define the preferences from two perspectives of a game. Let $V_u(\cdot)$ and $W_a(\cdot)$ denote the utility function of UE u and AP a respectively. After given there utilities, a user u prefers AP a_1 to a_2, if $V_u(a_1) > V_u(a_2)$. Without loss of generality, we denote this preference as $a_1 \succ_u a_2$. Similarly, an AP a prefers UE u_1 to u_2, if $W_a(u_1) > W_a(u_2)$ and this can be written as $u_1 \succ_a u_2$.

From the UEs' side, each UE u can be served by several APs and seeks to maximize its own individual satisfaction function. Using the interference cancellation techniques and blockage introduced by Section II-B, one AP's choice will not affect the remaining APs' utilities and the matching game will have no *peer effects*. For each user, the individual satisfaction can be determined by its achievable data rate. Thus, for each AP $a \in \mathcal{A}$, we define the users' utilities as:

$$V_u(a) = BW \log_2(1 + SNR_{ua}) \tag{11}$$

where SNR_{ua} is SNR between AP a and UE u. The utility reveals that users only care the data rate. It is worth noting that the users' preferences will change as the wireless environment changes.

From the APs' side, each AP a can serve only one user and seeks to maximize its own individual contribution to the control plane of Local Access. In order to reduce the number of triggering event R1, LCC should predict users' preferences and notify APs. Subsequently, APs can determine the preferences for users. For each AP, it tends to select the user whose preferences are more suited to its own cached content. Therefore, for each user $u \in \mathcal{U}$, the access points' utilities are given by:

$$W_a(u) = \mathbf{v}_a^C \left((1 - \mathbf{v}_u^D) \odot \mathbf{v}_u^P\right)^T = \sum_{c\in\mathcal{C}} y_{ac}(1 - z_{uc})P_{uc} \tag{12}$$

Thus, the utility reflects the similarity between preferences and cached content. It is worth noting that the access points' preferences will change as the download history updates.

Given the formulated many-to-one matching game, our goal is to find a *stable matching*, which is a key concept in matching theory [26]. Thus, we define a stable matching as follows:

Definition 2: A matching μ is stable, if and only if no pair blocks the matching, That is, for any stable pair $(u, a) \in \mu$, $\nexists\, u' \in \mathcal{U}$ s.t. $u' \succ_a u$ and $a \succ_{u'} \mu(u')$, or $\nexists\, a' \in \mathcal{A}$ s.t. $a' \succ_u a$ and $u \succ_{a'} \mu(a')$

A stable matching solution indicates that no AP can benefit by changing its current serving UE and vice versa. In order to find a stable matching solution for AP cluster problem, based on deferred acceptance algorithm and collaborative filtering algorithm, we propose a CPR-based AP Clustering (CPRAC) algorithm.

According to definition 2, our proposed CPRAC algorithm is guaranteed to converge to a local stable matching, which is shown in Algorithm 1.

Algorithm 1 CPR-Based AP Clustering (CPRAC) Algorithm

Initialization: NDC gathers content download history of all registered users and save as entries in databases, NCC queries the entries from these databases and calculates users' preferences based on CPR, and notifies LCC. Then, LCC sends the user preference list to all APs.
End initialization
while $\mu(n) \neq \mu(n+1)$ **do**
  for Each AP a **do**
    Calculates its own utility vector and constructs its preference lists based on (13) and sends a proposal to its most favored user.
  end for
  for Each UE u **do**
    Calculates the utilities for all APs who are sent proposals to UE u. Ranks those utilities with the utilities from APs who has served u before as a list and calculate the size of the list as N_a.
    if $N_a > N_a^{max}$ **then**
      select the top N_a^{max} and withdraw others.
    else
      select them all
    end if
  end for
  for Each AP a **do**
    if Withdrew by UE u **then**
      sets the utility $W_a(u) = 0$ and never sends a proposal to user u
    end if
  end for
  Form a new matching $\mu(n+1)$
end while
Return Stable matching μ^*.

Proof: The numbers of APs and UEs are limited, hence, all possible matching pairs are limited. Moreover, for a return matching μ^*, if μ^* is not a stable matching, there must be a blocking pair (u,a) that blocks our matching μ^*. Thus, $u \succ_a \mu^*(a)$ and $a \succ_u \mu^*(u)$. If $u \succ_a \mu^*(a)$, it means that AP a has sent a proposal to UE u before sending a proposal to UE $\mu^*(a)$ due to the structure of the preference vector. That is, AP a has already been rejected by UE u. Now let us assume that AP a has been withdrawn by UE u due to AP a', which means $a' \succ_u a$. Let the utility provided by a' is $V_c(a')$. Therefore, in the final matching only someone having a utility higher than $V_u(a')$ can be associated to u, which means $\mu^*(u) \succ_u a$. This contradicts with our initial assumption and (u, a) is not a blocking pair. Therefore, μ^* is a stable matching. □

B. SHORTEST PATH-BASED INTRA-CLUSTER ENERGY COOPERATION

After AP cluster, those APs in APC are still possible to handover because of triggering event R2. In order to reduce the number of triggering event R2, we propose a suboptimal solution with intra-cluster energy cooperation. For each APC, the aggregator can transfer the energy harvested by those fully charged AP to the AP with insufficient energy, which can effectively prevent triggering event R2.

In order to average the energy of all the APs in each APC, we employ a the greedy algorithm for energy cooperation. For the sake of simplicity, we assume all APs harvest same amount of power from the environment , i.e., $P_a^{in} = P^{in}$, and we superimpose the harvested energy on the energy of the battery.

In our shortest path-based energy cooperation (SPEC) algorithm, the lowest energy AP in each cluster sends a request to the highest energy AP to obtain energy in each iteration. We assume identical transferred energy in each iteration, denote as ε. It is worth noting that the energy losses of each AP pair are different, here, we define a loss transfer efficiency matrix $\mathbf{H_l}$, which can be given as:

$$\mathbf{H_l} = \begin{bmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1n} \\ \beta_{21} & \cdots & \cdots & \beta_{2n} \\ \cdots & \cdots & \beta_{ij} & \cdots \\ \beta_{n1} & \beta_{n2} & \cdots & \beta_{nn} \end{bmatrix} \tag{13}$$

where β_{ij} represents the energy loss efficiency between AP i and AP j, in particular, $\beta_{ii} = 0$. As we can see, this is also a symmetric matrix. Hence, in order to minimize the energy loss, we use the Floyd-Warshall algorithm to find the best path for energy transfer. It is obvious that, after a finite number of iterations, the energy of all APs will be the same, and the algorithm terminates. The details of our SPEC algorithm are provided in algorithm 2.

C. IMPLEMENTATION

The overall social-energy based cluster management scheme for UUDN can be summarized as two steps. First, NDC gathers content download history of all registered users and save as entries in databases. Then, NCC will perform download history analysis function, that is, query the entries from these databases in NDC and predict users' preferences. After that, NCC sends these preferences as a data list to the LCC through IP routers. When received these preference list, LCC will streamline the preference list by excluding users without service and send the preference list to all connected APs. Next, LCC decides the APC for each registered user by CPRAC algorithm and notifies the NCC, while NCC allocates a unique APC-ID for each registered user's AP cluster. Once all the APCs have been formed, the LCC will begin

Algorithm 2 Shortest Path-Based Energy Cooperation (SPEC) Algorithm

Initialization: Aggregator gathers the loss transfer efficiency of all AP pairs and sends to LCC. Then, LCC formulates those data as a matrix of energy transfer efficiency. and calculate its *Shortest distance matrix* and *Routing matrix* by using Floyd-Warshall algorithm and set $i = 0$.
End initialization
repeat
The AP l with the lowest energy P_{min} send a proposal to the AP h with the highest energy P_{max}.
AP h transfer the energy to the AP l with ε through routing matrix.
until $\|P_{max} - P_{min}\| > \Delta$
Algorithm terminates

to perform the energy cooperation function. Meanwhile, the aggregator in Local Access will gather the energy transfer efficiency of all connected AP pairs and sends to LCC. Then, LCC formulates a matrix of energy transfer efficiency and stores it in LDC to facilitate future inquiries. Finally, the LCC completes the energy cooperation through the SPEC algorithm. Our scheme can guarantee the QoS of users and solve the signalling overload problem caused by dense AP deployment effectively at the same time.

V. PERFORMANCE ANALYSIS

In this section, we conduct simulations of the proposed clustered-based energy cooperation scheme in APC management of UUDN. In our simulation scenario, APs and UEs are randomly located within a square area of 1 Km^2, and the simulation parameters of the UDN model and mmWave model are listed in Table 2. In particular, according to [27],

TABLE 2. Simulated parameters.

Parameter	Value
Network Model	The downlink of a densesmall cell network environment where the small cell density λ_a is much larger than the users density λ_u
User Density λ_u	100 - 1000 users / Km^2
Small cells Density λ_a	10^3 - 10^6 cells / Km^2
Cluster size N_a^{max}	1 - 5
Small cells Power P_a	100 mwatts (20 dBm)
Cell Radius r	30 m
Antenna System	SISO
Main lobe width θ_m	1
Antenna gain of AP G_a	30 dBi
Antenna gain of UE G_u	5 dBi
Fading Channel Model	Rayleigh
Frequency	28 GHz
Bandwidth BW	20 MHz
Pathloss Exponent α_{LOS}	2.1
Noise spectral density	-174 dBm/Hz

the omnidirectional LOS path loss exponent α_{LOS} is 2.1 at 28 GHz. For each simulation scenario with the fixed APs and UEs, we average the simulations by 1000 times, and each time with the newly random-selected locations.

In order to show the efficiency of our proposed CPR-based AP cluster algorithm, we compare the performance of our scheme with two following schemes:

1) **Average Selection** (AS): Since each AP can only serve one user at a time, APs preferentially serve those UEs with fewer candidate AP sets to maximize the minimum transmission rate of users.
2) **Random Selection** (RS): APs uniform randomly serve UEs based on radius limits.

We also evaluate the performances of social domain on three benchmark datasets, including **Movielens** (http://www.grouplens.org/), **Netflix** (http://www.netflixprize.com/) and **Amazon** (http://www.amazon.com/). In order to capture users preferences and recommend objects more precisely, they all leverage ratings from 1 to 5 stars. Here we only consider objects collected by users with ratings at least 3 stars. Before the experiments, datasets are randomly divided into two parts: a training set containing 90% links and a testing set containing the rest 10%. Recommendation results are generated by training set and evaluated by testing set. After processing, detailed information of the datasets is shown in Table 3.

TABLE 3. Primary information of the three datasets.

Data	Movielens	Netflix	Amazon
Items	1543	10000	4000
Users	943	5640	3603
Training set links	74718	634029	110011
Testing set links	7802	67918	10424

A. RECOMMENDATION

In order to show the satisfactory performance of our proposed algorithm, we compared the performance of our scheme, labeled as **Congeniality-based Personalized Recommendation** (CPR) with the following algorithms:

1) **Global Ranking Method** (GRM), [28], [29]: where all the objects are sorted in the descending order of degree, and those with highest degrees will be recommend. GRM algorithm lacks personalization, but it is simple and widely used. GRM algorithm only considers the most downloaded content and thinks users prefer the most downloaded content. For each content c, the download times N_c^D can be written as:

$$N_c^D = \sum_{u \in \mathcal{U}} \mathbf{v}_u^P(c) \tag{14}$$

Therefore, the preference of each user u to content c is given by:

$$P_{ic}^{GRM} = \frac{N_c^D}{\sum_{c \in \mathcal{C}} N_c^D} \tag{15}$$

TABLE 4. Demographic Prediction performance comparison by three evaluation metrics.

RLL	Method	Movielens			Netflix			Amazon		
		Precision	Recall	$< r >$	Precision	Recall	$< r >$	Precision	Recall	$< r >$
L=10	GRM	0.0824	0.0996	0.1457	0.0250	0.0208	0.2052	0.0045	0.0154	0.3629
	CF	0.1247	0.1507	0.1195	0.0387	0.0321	0.1760	0.0324	0.1120	**0.1213**
	CPR	**0.1609**	**0.1944**	**0.0975**	**0.0682**	**0.0567**	**0.1362**	**0.0362**	**0.1250**	0.1274
L=50	GRM	0.0523	0.3163	0.1457	0.0161	0.0670	0.2052	0.0036	0.0626	0.3629
	CF	0.0663	0.4007	0.1195	0.0238	0.0987	0.1760	0.0157	0.2721	**0.1213**
	CPR	**0.0776**	**0.4691**	**0.0975**	**0.0366**	**0.1521**	**0.1362**	**0.0168**	**0.2902**	0.1274
L=100	GRM	0.0383	0.4630	0.1457	0.0137	0.1136	0.2052	0.0030	0.1028	0.3629
	CF	0.0452	0.5467	0.1195	0.0185	0.1533	0.1760	0.0111	0.3841	**0.1213**
	CPR	**0.0516**	**0.6233**	**0.0975**	**0.0269**	**0.2233**	**0.1362**	**0.0114**	**0.3948**	0.1274

2) **Collaborative Filtering** (CF) : where users' nearest neighbors are found based on history profile and according to their neighbors' interests to predict their preferences with cosine similarity. The preference of each user u to content c is given as follow:

$$P_{uc}^{CF} = \sum_{u' \in \mathcal{U}, u' \neq u} S_{uu'} z_{u'c} \tag{16}$$

where $S_{uu'}$ is defined in Eq. (6).

The results are reported in Table 4. It is easy to find that the experimental results are very similar under different recommendation list lengths L. As shown in the table, we use three metrics to measure our recommended performance:

1) Precision [30]: Precision measures the ratio of the number of the recommended testing links contained in the top-L recommendation list for an arbitrary user.
2) Recall [31]: Recall is the proportion of the number of all hitting links in testing set and the size of testing set.
3) Averaged ranking score $< r >$ [32] : $< r >$ measures the average ranking of links in testing set in recommendation lists.

In Table 4, compared with CF, our proposed algorithm increases the precision and recall by 29.03%, 29.00% for *Movielens*, 76.23%, 76.64% for *Netflix* and 11.73%, 11.61% for *Amazon* when recommendation list lengths L is 10. When recommendation list lengths L increases to 50, CPR increases the precision and recall by 17.04%, 17.07% for *Movielens*, 53.78%, 54.10% for *Netflix* and 7.01%, 6.65% for *Amazon*. It is worth noting that the *Amazon* data set reflects that people prefer to buy books in their favorite areas, thus, it is more suitable for using item-based recommendation algorithms. *Movielens* and *Netflix* reflect the taste of people watching movies and browsing web, which are more suitable for represent download history. Therefore, in our simulation, we use the training set of Movielens as the download history in NDC and the testing set of Movielens as the future request in next time interval T. Since the number of items is 1574, we assume each AP randomly caches 500 content ($N_c^{max} = 500$). In addition, It can be easily found that our proposed algorithm CPR has a significant improvement in the recommended performance compared to CF and GRM.

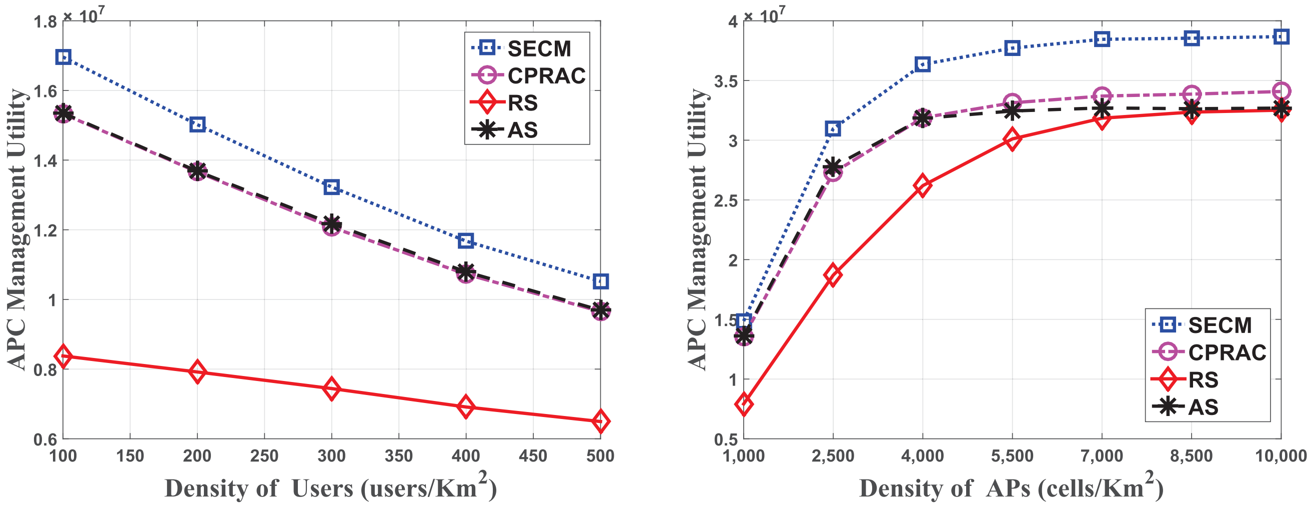
B. APC MANAGEMENT UTILITY

In order to validate our proposed SECM in APC management utility maximization, we compare its performance with three other algorithms, namely RS, AS, CPRAC. The APC management utility can be given as:

$$U_u = \sum_{a=1}^{A} x_{ua} \left(BW \log_2(1 + SNR_{ua}) - w_1 \mathcal{C} \frac{n_a}{T} \right) \tag{17}$$

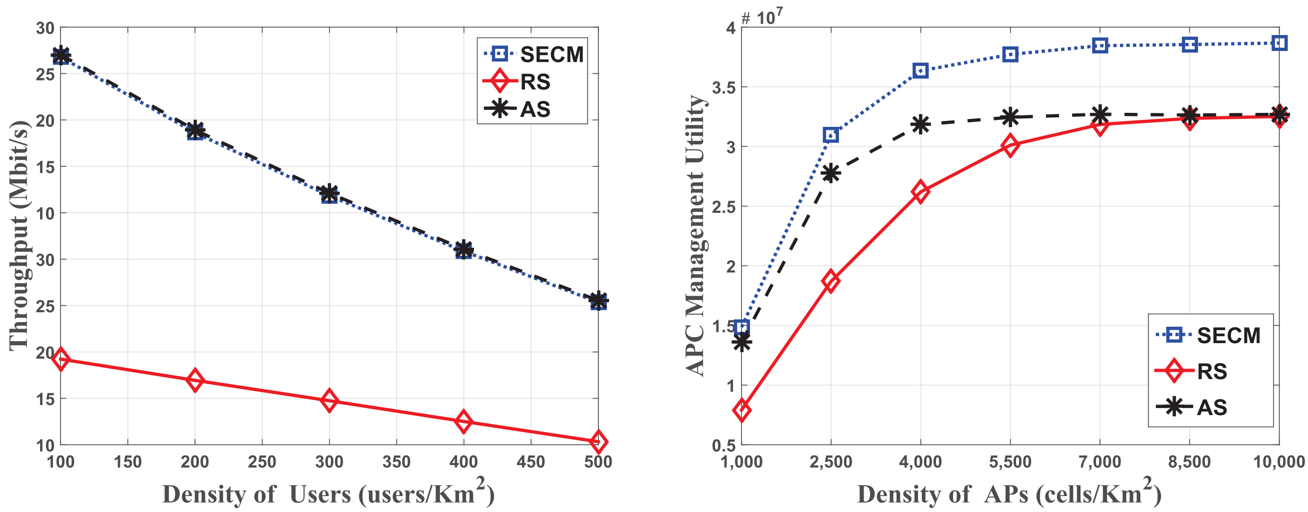
where $\mathcal{C}$ is the overhead caused by one AP handover in control plane. $\sum_{a=1}^{A} x_{ua} \left(BW \log_2(1 + SNR_{ua}) \right)$ represents the total throughput of APC serving UE u and $\sum_{a=1}^{A} x_{ua} \left(w_1 \mathcal{C} \frac{n_a}{T} \right)$ represents the total AP handover times of this APC. In our simulation, we use the training set of Movielens as the download history in NDC and the testing set of Movielens as the future request in next time interval T.

In fig. 3(a), when the cluster size equals to 5 and the density of APs equals to 1000 cells / Km^2, the APC management utility of SECM is higher than AS and CPRAC, with about 8.6% and 10.0%. Although AS can achieve nearly throughput performance with SECM, AS can lead to an increase of the APC update frequency. Similar to AS, CPRAC increases the APC update frequency due to lacking of energy cooperation. RS algorithm performs worst, as it neither considers the throughput of APC nor considers the overhead of APC updating. SECM performs better than RS about 77.8% in average. We also note that the APC management utility decreases with the growing density of UEs. The reason is that as the number of UEs increases, the size of APC decreases and the throughput of each APC decreases. From Fig. 3(b), the increasing density of APs from 1000 to 5500 can bring significant performance improvement, while continuing to increase the AP density from 5500 to 10000 makes the system performance close to saturation. Compared with the other schemes, we can observe that our proposed scheme of SECM



(a) (b)

FIGURE 3. **APC management utility with different clustering algorithms in the case of varying the density of UEs and APs. (a) $N_a^{max} = 5$ and $\lambda_a = 1000$ cells / Km^2. (b) $N_a^{max} = 5$ and $\lambda_u = 200$ users / Km^2.**



(a) (b)

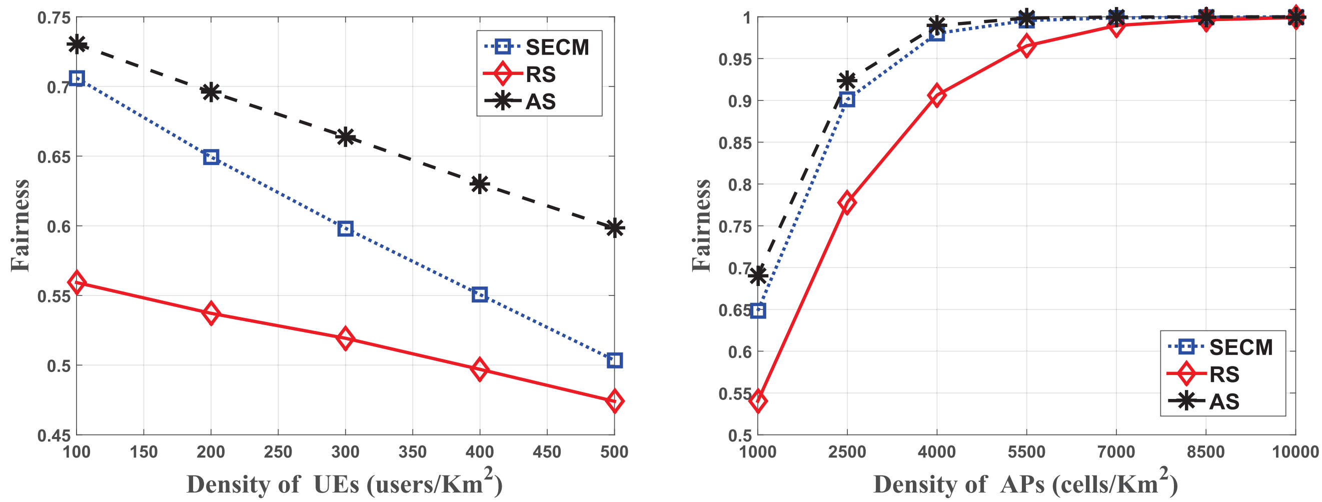
FIGURE 4. **Average throughput of each user with different clustering algorithms in the case of varying the density of UEs and APs. (a) $N_a^{max} = 5$ and $\lambda_a = 1000$ cells / Km^2. (b) $N_a^{max} = 5$ and $\lambda_u = 200$ users / Km^2.**

always achieves the best performance. When the density of APs is large enough (e.g. $\lambda_a = 10000$ cells / Km^2), SECM outperforms RS and AS about 18.3% and CPRAC about 13.5%. The reason is that as the density of APs increases, the throughput of each APC approaches equal, but other schemes do not consider energy cooperation, which can lead to APC update frequently, resulting in signaling overhead in control plane. Thus, these results demonstrate that our proposed SECM can achieve good performance of throughput with less signalling overhead.

C. THROUGHPUT

Then we analyze the average throughput of users under the three following schemes: RS, AS, CRPAC. We set the cluster size to be 5 and vary the density of UEs and APs, respectively. The performance of the average throughput is shown in Fig. 4(a) and Fig. 4(b), respectively.

The result indicates that the average throughput decreases with growing density of users, because the size of each APC decreases. In Fig. 4(a), we observe that the average throughput of SECM is very close to the AS and outperforms RS about 83.4%. Although the AS algorithm does not consider maximizing the throughput of each link, it can ensure the number of serving APs as large as possible, which still results in good performance. However, the increase in the number of service APs brings more the signalling overheads in control plane. RS algorithm has the worst performance since it neither maximizes the number of serving APs nor



(a) (b)

FIGURE 5. Fairness among users of different clustering algorithms in the case of varying the density of UEs and APs. (a) $N_a^{max} = 5$ and $\lambda_a = 1000$ cells / Km^2. (b) $N_a^{max} = 5$ and $\lambda_u = 200$ users / Km^2.

maximizes the data rate of each link. From Fig. 4(b), we see the average throughput increase due to the growing density of APs. The reason is that as the density of APs increases, each user can be served by more APs, in turn the advantages of AS and SECM no longer exist. Thus, the throughput of SECM, AS and RS become gradually equal when the density of APs reaches to 10000 cells / Km^2. We can also observe that SECM outperforms the other schemes, which reveals that in APC clustering, the proposed SECM can achieve higher throughput.

D. FAIRNESS

Jains fairness index [33] is employed to evaluate some insights on sharing of the throughput among APCs. We observe that changing the number of UEs or APs can affect the throughput fairness under SECM, AS, RS. In Fig. 5(a), we can observe that AS has the best fairness due to the sizes of the APC clusters are averaged. The fairness under all three schemes drop with increasing density of users. This is because the number of serving APs reduces, leading to a larger number of users without services. However, if the density of the AP increases, those can be served by more APs which can enhance the fairness, as shown in Fig. 5(b). Therefore, our algorithm can obtain good performance of throughput in data plane and less signalling overhead in control plane without the sacrifice of fairness.

E. APC UPDATE FREQUENCY

We proceed to evaluate the APC update frequency with varying density of UEs, APs and the size of the cluster. Fig. 6 shows that the APC update frequency decreases with increasing density of UEs. This is because the size of each APC reduces as the density of UE increases, thus the possibility of each APC update is reduced. Our proposed SECM performs better than CPRAC and AS about 10.4% in average. GECM scheme consists of GRM in AP cluster and SPEC in intra-cluster energy cooperation. Since the precision and recall of CPR is better than GRM, so the performance of SECM is better than GECM. Fig. 7 shows that APC update frequency increases as the size of cluster enlarges. Because there are higher possibilities for triggering event R1 or R2. We observe that RS always has the lowest frequency, since RS reduces the number of serving APs. AS and CPRAC always achieve the worst performance. The reason is that the number of serving APs is large under AS, which can increase the possibility of APC update. Compared to other schemes, CPRAC does not consider energy cooperation, as a result, it is easier to trigger event R2. We also see that the APC update frequency of SECM is slightly smaller than GECM. This is consistent

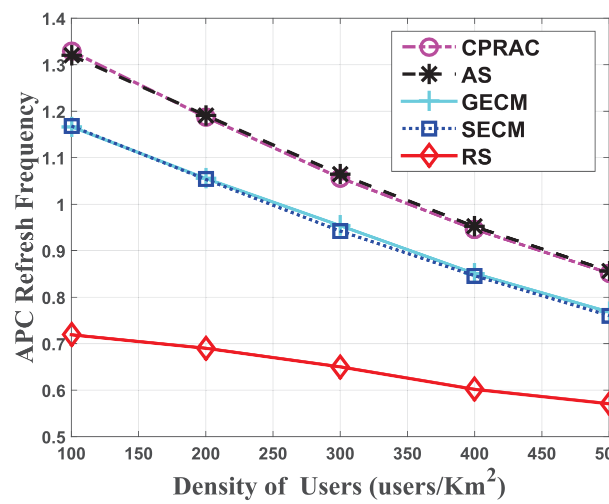


FIGURE 6. APC update frequency among APC of clustering algorithms in the case of varying the density of Users.

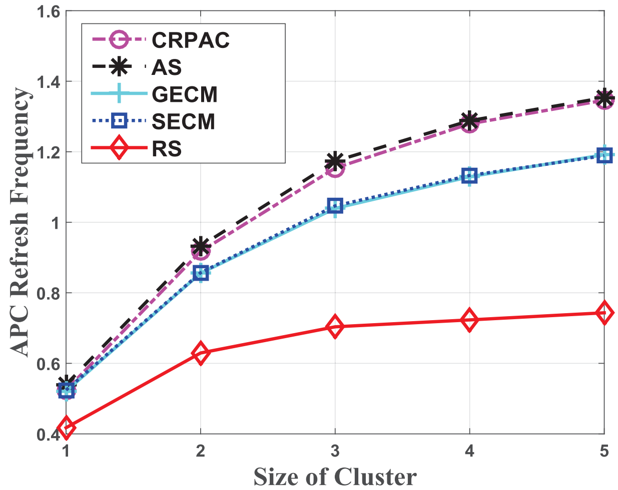


FIGURE 7. APC update frequency among APC of clustering algorithms in the case of varying the size of cluster.

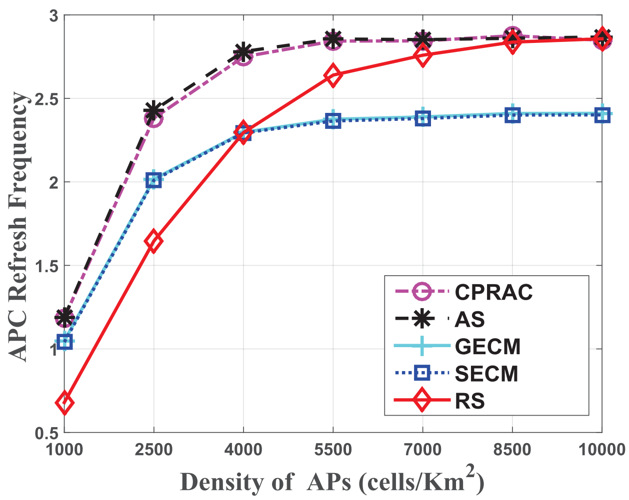


FIGURE 8. APC update frequency among APC of clustering algorithms in the case of varying the density of APs.

with the conclusion of section IV-A. Accurate prediction of user preference helps to reduce the probability of event R1 triggering. Fig. 8 shows that APC update frequency increases with growing density of APs. Because APC is more likely to be updated with increasing size of cluster. Since the RS does not consider the social domain nor the energy domain, the APC update frequency will be the same as that of AS.

VI. CONCLUSION

UDN is a promising solution towards 5G networks. Based on the analysis of the user-centric UDN, we propose a novel social-energy based cluster management scheme. Particularly, it consists of social-aware clustering and inter-cluster energy cooperation. By formulating a matching game problem in social-aware clustering, we propose a CPR-based AP cluster algorithm. Based on theoretical analysis, we prove the our algorithm is guaranteed to converge to a local stable matching. Then, we propose a inter-cluster energy cooperation scheme. Simulation results show that our proposed scheme can achieve a gain of 77.8% in the APC management utility averagely, without loss of fairness compared with other state-of-the-art schemes. When the density of APs is large enough, SECM outperforms RS and AS about 18.3% and CPRAC about 13.5%.

For future work, in order to further reduce the handover times of AP and decrease signaling overhead of the control plane, more comprehensive context information and more complicated learning algorithms need to be used to achieve more accurate predictions. In addition, for high density of AP, a flexible backhauling scheme to support non-ideal, wireless backhaul is very important to ensure the deployment. Another challenge is the accurate modelling of wireless channel. Both LOS and NLOS transmissions should be considered with not only Rayleigh model but also Rician and Nakagami-m fading models. Moreover, APs and UEs are equipped with MIMO is another key issue for AP cluster.

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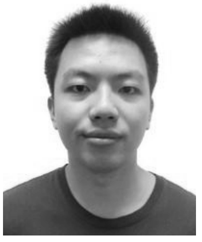

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