Social-aware Cooperative Caching in Fog Radio Access Networks

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***Abstract*—In this paper, the cooperative caching problem in fog radio access networks (F-RANs) is investigated to jointly optimize the transmission delay and energy consumption. Exploiting the potential social relationships among fog access points (F-APs), we firstly propose a clustering scheme based on hedonic coalition game (HCG) to improve the potential cooperation gain. Then, considering that the optimization problem is non-deterministic polynomial hard (NP-hard), we further propose an improved firefly algorithm (FA) based cooperative caching scheme, which utilizes a mutation strategy based on local content popularity to avoid pre-mature convergence. Simulation results show that our proposed scheme can effectively reduce the content transmission delay and energy consumption in comparison with the baselines.**

***Index Terms*—Fog radio access networks, cooperative caching, social-aware, hedonic coalition game, firefly algorithm.**

I. Introduction

With the rapid popularization of intelligent mobile terminals and the continuous development of application services, wireless networks are undergoing tremendous data traffic pressure. The unprecedented data traffics especially bring huge traffic congestion to the fronthaul links. Fog radio access network (F-RAN) is regarded as a promising network architecture to effectively alleviate traffic congestion and reduce content delivery delay by deploying storage and computing resources in fog access points (F-APs) at the network edge [1]–[7]. To fully exploit the limited caching capacity, cooperative caching becomes a viable approach to decrease energy consumption and content delivery delay.

Recently, many studies have been carried out on cooperative caching. In [8], a cooperative edge caching scheme was proposed to minimize the average download delay by exploiting an improved pigeon inspired optimization (PIO) approach. In [9], a cooperative caching algorithm was proposed for clustered vehicular content networks, which was devised based on global caching status. In [10], a cooperative content placement problem was investigated to maximize the increasing offloaded traffic by utilizing a graph-based approach. In [11], by considering the stochastic information of network topology, a user-centric cooperative caching scheme was proposed to minimize the average content transmission delay. In [12], based on multi-agent reinforcement learning, a cooperative content strategy was proposed to maximize the average transmission delay reduction without the knowledge of user preference in advance. However, most of the above mentioned research works give several fixed clusters in advance, and do not form clusters through potential relationships among access points. Besides, the content diversity in access points will be further decreased without consideration of cooperation among multiple clusters.

Motivated by the aforementioned discussions, we propose a cooperative caching scheme to jointly optimize the transmission delay and energy consumption. We firstly utilize local content popularity, distance and transmission power of F-APs to measure their social relationships. Then, we propose a social-aware clustering scheme by exploiting hedonic coalition game (HCG) to improve the cooperation gain among F-APs. Due to the non-deterministic polynomial hard (NP-hard) property of the optimization problem, we further propose an improved firefly algorithm (FA) based cooperative caching scheme, which can obtain a better feasible solution with low computational complexity.

The rest of this paper is organized as follows. In Section II, the system model and problem formulation are briefly presented. In Section III, the proposed HCG-based clustering scheme is introduced. The improved FA-based cooperative caching scheme is presented in Section IV. Simulation results are shown in Section V. Conclusions are drawn in Section VI.

II. System Model and Problem Formulation

A. Network Model

As shown in Fig. 1, we consider a specific cooperative caching region in F-RANs, which consists of a cloud server, M F-APs and U users. The cloud server can collect relevant caching status information of the F-RANs, and broadcast the information to all F-APs in the considered region [13]. Let $\mathcal{M} = \{1, 2, \ldots, m, \ldots, M\}$ and $\mathcal{U} = \{1, 2, \ldots, u, \ldots U\}$ denote the F-AP set and the user set, respectively. If user u sends a content request to the nearest F-AP m, then F-AP m is referred to as the local F-AP of user u and user u is referred to as the local user of F-AP m. Let $\mathcal{U}_m$ denote the set of local users for F-AP m. By considering the intensive deployment of F-APs, they can cooperate with each other and form several disjoint clusters. Suppose that the considered F-APs can be divided into K disjoint clustered sets denoted as $\mathcal{S}_k$ for $k \in \{1, 2, \ldots, k, \ldots, K\}$. Then, we have: $\mathcal{M} = \bigcup_{k=1}^{K} \mathcal{S}_k$, $\mathcal{S}_k \bigcap \mathcal{S}_{k'} = \varnothing$, $\forall \mathcal{S}_k, \mathcal{S}_{k'} \subset \mathcal{M}, k \neq k'$.

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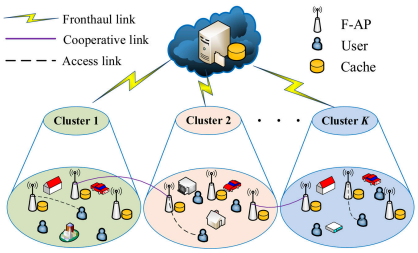


Fig. 1: Illustration of the cooperative caching scenario in F-RANs.

Without loss of generality, we assume that all the contents, which come from the content library $\mathcal{F} = \{1, 2, \ldots, f, \ldots F\}$ located in the cloud server, have the same size L. Let C denote the storage capacity of each F-AP, $p_{u,f}$ the probability of user u requesting for content f, and $p_{m,f}$ the probability that all local users of F-AP m send requests for content f (referred to as the normalized local content popularity of content f at F-AP m). Then, we have:

$$p_{m,f} = \frac{\sum_{u \in \mathcal{U}_m} p_{u,f}}{\sum_{f \in \mathcal{F}} \sum_{u \in \mathcal{U}_m} p_{u,f}}. \tag{1}$$

If the requested content has been stored in local F-AP of the same cluster, it will be directly transmitted to the requesting user via access link. If the requested content has been stored in other clusters, it will be delivered to local F-AP via cooperative link and forwarded to the requesting user by local F-AP. If the requested content has only been cached in the cloud server, local F-AP will obtain the content from the cloud server via fronthaul link and forward to the requesting user.

In addition, in our network model, the content caching process is composed of two phases: content placement and content delivery. Since content placement phase usually occurs at off-peak time, it does not occupy content delivery time.

B. Content Delivery

Let R denote the average transmission rate of contents fetched from the cloud server. Let $r_{m,u}$ denote the distance between F-AP m and user u, and $r_{m,n}$ the distance between F-AP m and F-AP n. Let B_1 and B_2 denote the transmission bandwidths of access link and cooperative link, respectively. Let P_m denote the transmission power of F-AP m, σ^2 the noise power, I the sum of interfering signal power from neighboring F-APs, and α the pathloss exponent. Let $R_{m,u}$ denote the achievable content transmission rate of the access link between F-AP m and user u. Then, it can be expressed as $R_{m,u} = B_1 \log_2\left(1 + P_m r_{m,u}^{-\alpha} / \left(\sigma^2 + I\right)\right)$. Let $R_{m,n}$ denote the achievable content transmission rate of the cooperative link between F-AP m and F-AP n. Then, it can be expressed as $R_{m,n} = B_2 \log_2\left(1 + P_m r_{m,n}^{-\alpha} / \left(\sigma^2 + I\right)\right)$.

Let $x_{m,f}$ denote the binary cache decision variable with $x_{m,f} = 1$ if F-AP m has cached content f and $x_{m,f} = 0$ otherwise. For the sake of simplicity, we define $x_{k,f} = 1 - \prod_{m \in \mathcal{S}_k} (1 - x_{m,f})$ [10]. Specifically, if cluster S_k has cached content f, we have $x_{k,f} = 1$. Otherwise, $x_{k,f} = 0$.

If user u requests content f which has been stored in local cluster $\mathcal{S}_k$, the transmission delay can be expressed as follows:

$$T_1 = x_{k,f} L / R_{m,u}. \tag{2}$$

If the requested content has not been cached in local cluster $\mathcal{S}_k$ and has been stored in another cluster $\mathcal{S}_{k'}$, the transmission delay can be expressed as follows:

$$T_2 = (1 - x_{k,f}) \left[1 - \prod\nolimits_{\mathcal{S}_{k'} \subset \mathcal{M}} (1 - x_{k',f})\right] \times \left(1/R_{m,n} + 1/R_{m,u}\right) L. \tag{3}$$

If the requested content has only been cached in the cloud server, the transmission delay can be expressed as follows:

$$T_3 = (1 - x_{k,f}) \prod\nolimits_{\mathcal{S}_{k'} \subset \mathcal{M}} (1 - x_{k',f}) \times \left(1/R + 1/R_{m,u}\right) L. \tag{4}$$

Then, according to [8], the average transmission delay for obtaining the requested contents can be expressed as follows:

$$T = \sum_{u \in \mathcal{U}} \sum_{f \in \mathcal{F}} p_{u,f} \left(T_1 + T_2 + T_3\right). \tag{5}$$

C. Energy Consumption

We adopt the energy consumption model in [14]. Let E_{c} denote the energy consumption for content caching. Then, it can be expressed as follows:

$$E_{\mathrm{c}} = \sum_{m=1}^{M} \sum_{f=1}^{F} x_{m,f} J_{\mathrm{c}} L, \tag{6}$$

where J_{c} is the power coefficient of cache hardware.

When content f is transmitted to the requesting user u, the energy consumption is divided into three parts. If the requested content has been stored in local cluster $\mathcal{S}_k$, the energy consumption for content delivery can be expressed as follows:

$$E_1 = x_{k,f} L P_m / R_{m,u}. \tag{7}$$

If the requested content has been stored in another cluster $\mathcal{S}_{k'}$, the energy consumption for content delivery can be expressed as follows:

$$E_2 = (1 - x_{k,f}) \left[1 - \prod\nolimits_{\mathcal{S}_{k'} \subset \mathcal{M}} (1 - x_{k',f})\right] \times \left(1/R_{m,n} + 1/R_{m,u}\right) P_m L. \tag{8}$$

If the requested content has only been cached in the cloud server, the energy consumption for content delivery can be expressed as follows:

$$E_3 = (1 - x_{k,f}) \prod\nolimits_{\mathcal{S}_{k'} \subset \mathcal{M}} (1 - x_{k',f}) \times \left(P_{\mathrm{s}}/R + P_m/R_{m,u}\right) L, \tag{9}$$

where P_{s} denotes the average transmission power of contents fetched from the cloud server.

Correspondingly, the system energy consumption for ob-

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taining the requested contents can be expressed as follows:

$$E = E_{\mathrm{c}} + \sum_{u\in\mathcal{U}}\sum_{f\in\mathcal{F}} p_{u,f}\left(E_1 + E_2 + E_3\right). \tag{10}$$

D. Problem Formulation

To minimize the transmission delay and energy consumption, the corresponding cooperative caching optimization problem can be formulated as follows:

$$\min_{x_{m,f}} \mu T + (1-\mu)E, \tag{11}$$

$$\text{s.t.} \sum_{f=1}^{F} x_{m,f} L \le C, \forall m \in \mathcal{M}, \tag{11a}$$

$$x_{m,f} \in \{0,1\}, \forall m \in \mathcal{M}, \forall f \in \mathcal{F}, \tag{11b}$$

where μ is the scalar weight to ensure the same range for the transmission delay and energy consumption.

III. Proposed Social-aware Cooperative Caching Scheme

The optimization problem in (11) has two-fold challenges. First, the formation of clusters is unknown and giving fixed clusters in advance does not improve the caching performance. Second, the optimization problem has the NP-hard property and exponential computational complexity is required for finding the optimal solution. To overcome the two-fold challenges, in the following subsections, we solve the optimization problem by optimizing the formation of clusters and content placement separately.

A. Proposed HCG-based Clustering

In order to optimize the formation of clusters, we firstly measure the social relationships among F-APs and define the social preferences of F-APs for clusters. Then, we model the formation of clusters as a hedonic coalition game and propose a HCG-based clustering scheme.

1) Social Preference: Social networks are theoretical constructions composed of units and ties, which have been widely applied to study the relationships among groups or communities. F-APs can be considered as social units and the relationships among F-APs can be considered as ties [15]. Inspired by [16], we extend the social relationships among users to F-APs.

According to stochastic geometry theory, the position of user is modeled as an independent homogeneous Poisson distribution with the density λ_u. Then, the probability of user u contacting a potential partner can be expressed as follows:

$$p_{u,u'} = 1 - \exp\left(-\lambda_u \pi {d_{u,u'}}^2\right), \tag{12}$$

where $d_{u,u'}$ denotes the distance between user u and u'. Let $p_{m,n}$ denote the probability of the associated user in F-AP m communicating with the associated user in F-AP n, which can be expressed as follows:

$$p_{m,n} = \sum_{u\in\mathcal{U}_m}\sum_{u'\in\mathcal{U}_n} p_{u,u'}. \tag{13}$$

Let $\boldsymbol{s}_m = [p_{m,1}, p_{m,2}, \ldots, p_{m,f}, \ldots, p_{m,F}]^T$ denote the sequence of local content popularity in F-AP m. Let $\rho_{m,n}$ denote the content popularity similarity of the associated users in F-AP m and n, which can be expressed as follows:

$$\rho_{m,n} = \frac{\mathbb{E}\left[\left(\boldsymbol{s}_m - \mu(s_m)\right)^T\left(\boldsymbol{s}_n - \mu(s_n)\right)\right]}{\sigma\left(s_m\right)\sigma\left(s_n\right)}, \tag{14}$$

where $\mu(\cdot)$ denotes the mean of the local content popularity sequence, $\sigma(\cdot)$ the variance and $\mathbb{E}[\cdot]$ the expectation. Let $g_{m,n}$ denote the social contribution between F-AP m and n, which can be expressed as follows:

$$g_{m,n} = p_{m,n}\rho_{m,n}. \tag{15}$$

The social loss is defined as the caching and transmission overhead consumed by the cooperative transmission among F-APs. Then, it can be expressed as follows:

$$c_{m,n} = \sum_{f\in\mathcal{F}}\sum_{u\in\mathcal{U}_m}\left(p_{u,f}J_{\mathrm{c}} + \frac{P_m}{R_{m,n}}\right)L. \tag{16}$$

Meanwhile, considering the impact of distance on social relationship, we can define the social relationship of F-AP m and F-AP n as follows:

$$\psi_{m,n} = \begin{cases} e^{-\frac{d_{m,n}}{d_{\mathrm{th}}}}\left(g_{m,n} - \delta c_{m,n}\right), & d_{m,n} \le d_{\mathrm{th}}, \\ 0, & d_{m,n} > d_{\mathrm{th}}, \end{cases} \tag{17}$$

where δ denotes the social parameter according to the relative importance between social gain and loss, d_{mn} the distance between F-AP m and F-AP n, and d_{th} the distance threshold. Since two F-APs can forward data for each other, we believe that they are mutually trustworthy and the social preference is equivalent between F-AP m and F-AP n. The mutual social preference between two F-APs can be expressed as follows:

$$u_m(n) = u_n(m) = \begin{cases} \psi_{m,n} + \psi_{n,m}, & m \ne n, \\ 0, & m = n. \end{cases} \tag{18}$$

Obviously, the social preference is symmetric and additively separable [17]. Correspondingly, F-AP m's social preference for cluster $\mathcal{S}_k$ can be expressed as follows:

$$U_m(\mathcal{S}_k) = \sum_{n\in\mathcal{S}_k} u_m(n). \tag{19}$$

2) Proposed HCG-based Clustering: Hedonic coalition game is known as a class of coalition formation game, which allows the formation of coalition by utilizing the individual preferences of the players [18]. If the coalition formation game is hedonic, the preference of any player depends only on the other members of the coalition that the player belongs to. Besides, the formation of the coalition is the consequence of the player's preference for possible coalition sets [17]. The F-APs and clusters are equivalent to players and coalitions, respectively. Since the social preference of each F-AP for cluster $\mathcal{S}_k$ depends entirely on local content popularity, distance and transmission power of other members in the same cluster, the formation of cluster can be modeled as a HCG.

Let Π denote a coalition partition of the F-AP set $\mathcal{M}$,

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which is equivalent to the set of K disjoint clusters. Given a coalition partition Π and a player m, let $\mathcal{S}_\Pi(m)$ denote the current cluster $\mathcal{S}_k$ to which F-AP m belongs, and $\mathcal{S}_\Pi(m) \in \Pi$ such that $m \in \mathcal{S}_\Pi(m)$ [18]. F-AP m's social preference over possible clusters can be shown by an order $\succeq_m$, which is a reflexive, transitive and complete binary relation. Meanwhile, let $\succ_m$ denote the corresponding asymmetric relation. If F-AP m prefers to be a part of cluster $\mathcal{S}_k$ rather than cluster $\mathcal{S}_{k'}$, the relationship can be established as follows:

$$\mathcal{S}_k \succeq_m \mathcal{S}_{k'} \Leftrightarrow \sum_{n\in\mathcal{S}_k} u_m(n) \geq \sum_{n\in\mathcal{S}_{k'}} u_m(n). \tag{20}$$

In order to investigate the stability of hedonic game in the considered model, we introduce some concepts taken from [17]: 1) If there does not exist $m \in \mathcal{M}$ and a coalition $\mathcal{S}_k \in \Pi \cup \{\varnothing\}$ such that $\mathcal{S}_k \cup \{m\} \succ_m \mathcal{S}_\Pi(m)$ and $\mathcal{S}_k \cup \{m\} \succeq_n \mathcal{S}_k$ for all $n \in \mathcal{S}_k$, a coalition partition Π is individually stable. 2) If the players' preferences are symmetric and additively separable, there exists a coalition partition which has individual stability. 3) Depending on the stability of the individual, if player m can join the coalition without worsening the situation of any existing members, the coalition is considered to be open to player m, otherwise closed. Since the social preference is symmetric and additively separable, there exists an individually stable partition of cluster.

According to the above analysis, we propose a clustering scheme based on HCG. Firstly, we randomly divide the F-AP set into several subsets. Then, we calculate the social preferences of F-AP m for each cluster and find out S clusters whose social preferences are greater than the current cluster $\mathcal{S}_\Pi(m)$. If these clusters are open to F-AP m, F-AP m is transferred into its preferable cluster. Repeat the above operations until the cluster partition is individually stable. The detailed description of the proposed clustering scheme is shown in Algorithm 1.

Let P denote the maximum number of iterations when the partition is individually stable. Then, the computational complexity of the proposed HCG-based clustering scheme can be calculated to be $\mathcal{O}(PMK)$.

Algorithm 1 Proposed HCG-based Clustering Scheme

Input: the F-AP set $\mathcal{M}$;
Initialize: Randomly divide $\mathcal{M}$ into several subsets;
Calculate F-AP m's preference $u_m(n)$ with other F-APs;
repeat
  for m = 1 : M **do**
    Calculate F-AP m's preference $U_m(\mathcal{S}_k)$;
    Find clusters with preference greater than $\mathcal{S}_\Pi(m)$;
    Sort the obtained S clusters in descending order;
    for s = 1 : S **do**
      if $\mathcal{S}_k$ is open to F-AP m **then**
        $\mathcal{S}_\Pi(m) \rightarrow \mathcal{S}_\Pi(m)\backslash\{m\}$, $\mathcal{S}_k \rightarrow \mathcal{S}_k \cup \{m\}$;
      end if
    end for
    update cluster partition Π;
  end for
until Individual Stability;
Output: Individually stable coalition partition Π.

B. Proposed Improved FA-based Cooperative Caching

Since the optimization problem in (11) is NP-hard, it can not be solved in polynomial time. On the other side, the swarm intelligence algorithms do not rely on the analyticity of the optimization problem and can readily address the large-scale and complex problems which are difficult to be solved by brute force approaches [8]. Hence, we propose a cooperative caching scheme through a swarm intelligence algorithm, i.e., the improved firefly algorithm, which can solve the optimization problem with lower computational complexity. Note that swarm intelligence algorithms can not always guarantee to find the global optimum. Our proposed improved firefly algorithm can increase the chance of convergence to the optimal solution.

The original FA was proposed in [19] to mimic the process of firefly flash. The position of each firefly represents a feasible solution of the optimization problem, and the brightest firefly is a better feasible solution to the optimization problem. However, the original FA has some limitations. In the early stage of the iteration, if the brightness of a firefly greatly exceeds the average brightness of the current population, the firefly will quickly occupy an absolute proportion in the whole population. The diversity of the population rapidly decreases and the evolutionary ability will gradually disappear. Meanwhile, the search ability of FA depends mainly on the interaction between the firefly individuals, and the firefly lacks the corresponding mutation mechanism to get rid of the local extreme value.

To address the aforementioned issues, we propose an improved FA by utilizing the mutation strategy based on local content popularity. The key in our proposed strategy is to meet the integer constraint by heaviside step function and avoid premature convergence through the mutation strategy.

Let $\boldsymbol{X}^i = \left[x^i_{m,f}\right]_{M\times F}$ denote the ith firefly in each iteration, where $x^i_{m,f}$ denotes the ith caching status of content f in F-AP m. Let $\boldsymbol{X}^*$ denote the brightest individual firefly. Here we simply use the objective function value of the firefly's location as the firefly's brightness. Let I_i denote the brightness of the ith firefly. The attractiveness of firefly i to adjacent firefly j is associated with the brightness seen by adjacent firefly j, which varies with the distance between fireflies. Let $\beta_{i,j}$ denote the attractiveness of firefly i to firefly j, which can be expressed as follows [19]:

$$\beta_{i,j} = I_i e^{-\gamma r_{i,j}}, \tag{21}$$

where $r_{i,j} = ||\boldsymbol{X}^i - \boldsymbol{X}^j||_1$ is the manhattan distance between firefly i and j, and γ is the light absorption coefficient. In order to satisfy the integer constraint in (11b), we propose to improve the method of firefly location update by exploiting heaviside step function. Then, the movement of firefly j

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Algorithm 2 Proposed Improved FA-based Cooperative Caching Scheme

Initialize: Generate initial population of fireflies;
while not terminated **do**
  Evaluate individual light intensity I_i ;
  for $j = 1 : G$ **do**
    for $i = 1 : G$ **do**
      if $I_j < I_i$ **then**
        Calculate $\beta_{i,j}$ through (21);
        Calculate $\boldsymbol{X}^j$ through (22);
      end if
    end for
    if $\sum_{f=1}^{F} x_{m,f} L > C$, **then**
      Rank stored contents by local popularity;
      Remove redundant and unpopular content;
    elseif $\sum_{f=1}^{F} x_{m,f} L < C$, **then**
      Calculate the remaining storage space;
      Cache popular content;
    end if
  end for
end while
Output: The brightest firefly $\boldsymbol{X}^*$.

attracted to the brighter firefly i can be expressed as follows:

$$\boldsymbol{X}^j = H\left(\boldsymbol{X}^j + \beta_{i,j}\left(\boldsymbol{X}^i - \boldsymbol{X}^j\right) + \lambda\left(\epsilon - \frac{1}{2}\right) - \frac{1}{2}\right), \quad (22)$$

where λ is a randomization parameter, ϵ is a uniformly distributed random number which is between 0 and 1, and $H(x) = \begin{cases} 0, x < 0 \\ 1, x \geq 0 \end{cases}$ is the heaviside step function.

Once firefly falls into the neighborhood of the extreme point, it is difficult to jump out. To solve this issue, we propose to adopt the mutation strategy based on local content popularity. When a firefly flies to a new location according to (22), the caching status is likely to slightly exceed or be less than the storage capacity of F-AP m. If the content caching status in F-AP m slightly exceeds its storage capacity, the cached contents are sorted according to the local content popularity and the content with the lowest local content popularity will be deleted, i.e., $x^i_{m,f} = 1$ turns into $x^i_{m,f} = 0$. If the content caching status in F-AP m is less than its storage capacity, all contents are sorted according to the local content popularity and the uncached content with the highest local content popularity will be stored, i.e., $x^i_{m,f} = 0$ turns into $x^i_{m,f} = 1$. Through the above mutation strategy, the capacity constraint in (11a) can be satisfied. Meanwhile, the firefly can also easily jump out of the current local optimum and fly towards a better local optimum more quickly. The detailed description of the improved FA-based cooperative caching scheme is shown in Algorithm 2.

Let Q denote the maximum number of iterations, and G the size of firefly population. For the optimization problem in (11), the computational complexity of the exhaustive search approach is $\mathcal{O}(2^{MF})$. In contrast, the computational complexity of the improved FA-based cooperative caching scheme is $\mathcal{O}(QG^2)$. Generally, we have $F \gg G$, $F \gg Q$ and $M > 2$. Correspondingly, $QG^2 \ll 2^{MF}$ can always be guaranteed. Therefore, our proposed scheme has a significantly lower computational complexity than the traditional exhaustive search approach.

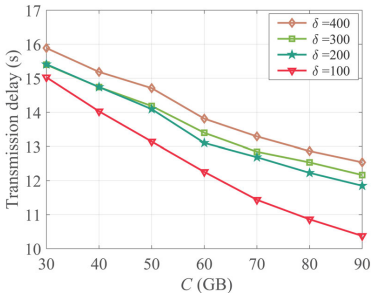


Fig. 2: Transmission delay vs. storage capacity with different δ.

IV. Simulation Results

In this section, the performance of the proposed cooperative caching scheme is evaluated via simulations. We consider a square area with side length of 1000 m and assume that the probability of user u requesting content f obeys Zipf distribution, i.e., $p_{uf} = \frac{R_f^{-\eta}}{\sum_{f' \in \mathcal{F}} R_{f'}^{-\eta}}$, where η denotes the skewness factor and R_f the rank of content f's popularity in a descending order [20]. The other system parameters are set as follows: $M = 15$, $U = 150$, $F = 1000$, $L = 500$ MB, $B_1 = B_2 = 10$ MHz, $\sigma^2 = -100$ dBm, $P_m = P_s = 46$ dBm, $\alpha = 4$, $J_c = 6.25$ pW/bit [14], $\mu = 0.01$, $\gamma = 0.001$. We choose the random caching (RC) scheme and PIO-based cooperative caching scheme [8] as the baselines for performance comparison.

In Fig. 2, we show the transmission delay of our proposed scheme versus storage capacity C with different social parameter δ. It can be observed that the transmission delay increases with δ. The reason is that when δ decreases, the proportion of social loss in social relationship is relatively decreased. Therefore, F-APs are more likely to cooperate with each other, and it is beneficial to consider social interaction among F-APs or clusters.

In Fig. 3, we show the convergence performance of our proposed scheme and the PIO-based scheme with $C = 50$ GB and $\eta = 0.5$. It can be observed that compared with the PIO-based scheme, the improved FA can converge to a near optimum with a faster speed. The reason is that based on local content popularity, our proposed mutation strategy improves the searching ability of FA.

In Fig. 4, we show the transmission delay of our proposed scheme and the baselines with different storage capacity C. It can be observed that the transmission delay of all the considered schemes decreases with storage capacity. The reason is

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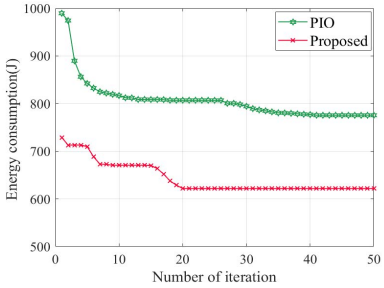


Fig. 3: Energy consumption vs. number of iterations.

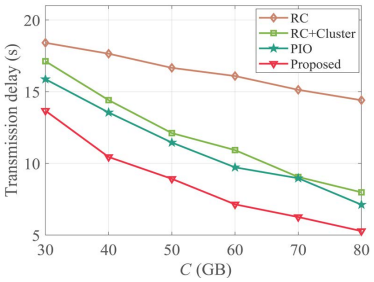


Fig. 4: Transmission delay vs. storage capacity with $\eta = 0.5$.

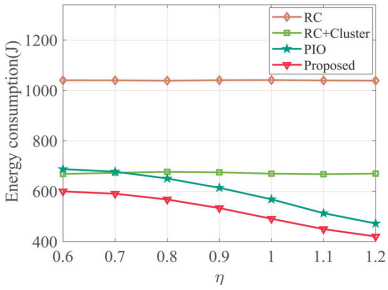


Fig. 5: Energy consumption vs. skewness factor with $C = 50$ GB.

that as the storage capacity becomes larger, the hit rate in the storage increases. It can also be observed that the proposed scheme is superior to the PIO-based scheme. The reason is that our proposed scheme can increase the cooperation gain among F-APs by exploiting the hidden social relationships.

In Fig. 5, we show the energy consumption of our proposed scheme and the baselines with different skewness factor η. It can be observed that our proposed scheme outperforms the PIO-based scheme and the RC scheme. The reason is that our formulated cooperative caching model allows cooperation among clusters, which can improve the content diversity in F-APs and reduce the overhead of content transmission among F-APs.

V. Conclusions

In this paper, we have proposed a social-aware cooperative caching scheme in F-RANs. Using the proposed HCG-based clustering scheme, we have reduced the transmission delay and energy consumption by increasing the cooperation gain among F-APs. In addition, using the proposed improved FA-based cooperative caching scheme, we have avoided premature convergence with low computational complexity. By utilizing the social relationships among F-APs and cooperation among clusters, our proposed scheme has provided considerable performance improvement over the baselines.

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