Efficient Interference-Aware D2D Pairing for Collaborative Data Dissemination

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***Abstract*—To offer a large capacity in the fifth-generation (5G) mobile networks, a promising technique is to integrate and utilize the intelligence and resources of smart devices at the mobile edge. In this paper, we investigate how to exploit device collaboration to facilitate data dissemination via device-to-device (D2D) communications. In particular, we focus on a key research problem that aims to effectively pair request devices with cache devices in close proximity. Due to the interference among D2D links, it is computationally hard to obtain an optimal pairing for a large-scale network. Hence, we propose an interference-aware approach that can obtain a near-optimal approximation result efficiently. Specifically, the proposed approach first uses Lagrangian relaxation to find an upper-bound solution, and then derives a feasible solution from the initial pairing and further augments it. Extensive simulation results show that our approach performs closely to the optimal solution and achieves significant performance gain over the existing schemes in terms of the ratio of matched device pairs and total sum rate.**

***Index Terms*—D2D communications, collaborative data dissemination, edge computing, device pairing, matching.**

I. Introduction and Related Work

Nowadays, the mobile networks become strained by a massive number of connected devices and a plethora of emerging applications. Meanwhile, the network is migrating to a data-centric paradigm and becomes dominated by data dissemination rather than end-to-end communications. To accommodate the unprecedented demands, a promising paradigm is to integrate and utilize the intelligence and resources of smart devices. The social relationships among end users can also facilitate the organization of smart devices for collaborative service delivery. Complementing this paradigm, device-to-device (D2D) communications further provide an effective supporting technique with various benefits in high data rates, energy saving, coverage expanding, and traffic offloading [1].

In the literature, there have been some existing works on data dissemination that leverages vehicle-to-vehicle (V2V) relay [2] or D2D communications [3]. In [2], a multi-hop broadcast solution is proposed for emergency message dissemination in vehicular ad hoc networks. In [4], Yu *et al.* also studies dissemination of time-critical messages over intermittently connected mobile networks. When D2D communications are involved in data dissemination, another important problem is the pairing of request devices with cache devices. For simplicity, many studies assume that a cache device can serve an arbitrary request device within a *collaboration distance*. In [3], Golrezaei *et al.* analyze the optimal collaboration distance for video content distribution over D2D communications by considering the trade-off between frequency reuse and the probability of finding the desired file on a nearby helper device. Nonetheless, this work adopts a simplified channel model, in which a square-sized cell is divided into a couple of clusters with equal size and only one active D2D link is allowed in each cluster. Such an interference-obliviousness solution may cause intolerable interference or cannot achieve the full potential of D2D communications in serving data dissemination. The work in [5] proposes an interference-aware approach for D2D device pairing. However, the heuristic nature of the approach cannot guarantee a high efficiency for some cases.

Based on the above insights, this paper aims to effectively tackle the mutual interference among D2D pairs while making the best use of the resources at cache devices. In particular, we propose an efficient interference-aware approach to obtain a device pairing for collaborative data dissemination with D2D communications. The device pairing is especially useful for social-aware content sharing. Our approach first uses Lagrangian relaxation to obtain an upper-bound solution. Then, a feasible solution is derived therein and further augmented by exploring remaining unpaired devices. We conduct extensive simulations to evaluate the performance of our proposed approach in different aspects. The simulation results show that this interference-aware approach can significantly improve the efficiency of D2D-assisted data dissemination, and it achieves performance fairly close to that of the optimal solution.

In the following, Section II gives the system model and problem formulation. Section III presents the proposed interference-aware approach. In Section IV, we evaluate the performance of the proposed approach and compare it with existing solutions. Section V concludes this paper.

II. System Model and Problem Formulation

A. Data Dissemination Scenario

In this paper, we consider a data dissemination scenario depicted in Fig. 1. A set of request devices, D, are requesting messages from set M. The request devices are randomly distributed in a circular region of radius R, which represents the coverage of a base station (BS) centered at the origin. Each

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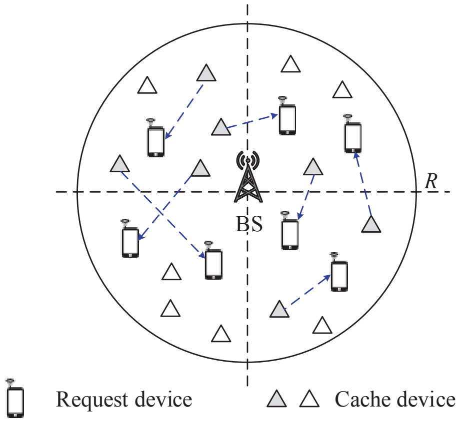

Fig. 1: Device pairing for D2D-assisted data dissemination.

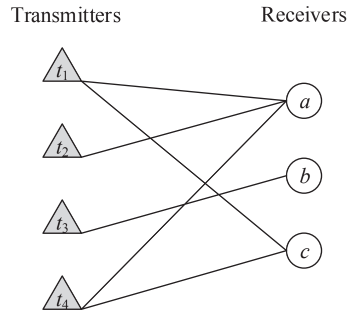

Fig. 2: A bipartite graph model for relationship between request devices and cache devices.

device $k \in D$ requests one message from set M independently according to a popularity distribution. In addition, there are a set of cache devices, S, in which each device $j \in S$ caches at most m_c messages from set M, e.g., according to the random caching policy studied in [3]. Since people are generally more willing to share data with their social connections, we assume that D has been screened so that each user in D has social ties with those in S. Then, instead of fulfilling each message request by the BS, it is potentially beneficial to serve some request devices in D by nearby cache devices in S via D2D communications. This D2D-assisted data dissemination can not only offload traffic from the BS but also save energy consumption with the close proximity.

B. D2D Channel Model

We consider a D2D underlaid cellular network, where the D2D links share the uplink spectrum of regular cellular users. Assume that all potential D2D transmitters of the cache devices in S share the same uplink channel of a cellular user that is uniformly located within coverage region of the cell. To offload message requests from the BS to cache devices, a request device can be paired to a feasible cache device that delivers the message content via D2D communications. Here, we define function $\varphi : S \mapsto D$ to represent the device pairing. Then, $\varphi(j) = k$ means that cache device $j \in S$ is selected to serve request device $k \in D$. The received signal at device k is thus written as

$$\begin{aligned} y_k =& \sqrt{P_d} d_{j,k}^{-\frac{\alpha}{2}} h_{j,k} x_k + \sqrt{P_c} d_{c,k}^{-\frac{\alpha}{2}} h_{c,k} x_c \\ &+ \sum_{j' \in S, j' \neq j} \theta_{j'} \sqrt{P_d} d_{j',k}^{-\frac{\alpha}{2}} h_{j',k} x_{\varphi(j')} + n_k. \end{aligned} \tag{1}$$

Here, α is the path-loss exponent, and n_k is the additive noise at D2D receiver k distributed as $\mathcal{CN}(0, \sigma^2)$. Besides, $\theta_{j'}$ is a binary variable indicating whether transmitter $j' \in S$ is selected to serve a request device. For D2D transmitter j and the cellular user using the same uplink channel, x_k and x_c are their sent signals, respectively, P_d and P_c are their respective transmit power, $d_{j,k}$ and $d_{c,k}$ are their respective distance to D2D receiver k, and $h_{j,k}$ and $h_{c,k}$ are the corresponding distance-independent channel gain that captures the fading effect. Considering Rayleigh fading channels, $|h_{j,k}|^2$ and $|h_{c,k}|^2$ follow an exponential distribution of unit mean.

In (1), the received signal at D2D receiver k includes the expected signal, the interference from the cellular user, the integrated interference from all other active D2D transmitters in S, and the additive noise. Hence, the signal-to-interference-plus-noise ratio (SINR) at D2D receiver k is given by

$$\Gamma_k = \frac{P_d d_{j,k}^{-\alpha} |h_{j,k}|^2}{P_c d_{c,k}^{-\alpha} |h_{c,k}|^2 + \sum_{j' \in S, j' \neq j} \theta_{j'} P_d d_{j',k}^{-\alpha} |h_{j',k}|^2 + \sigma^2}.$$

C. Device Pairing Problem

Our research problem is to obtain the pairing function $\varphi : S \mapsto D$ between the cache devices in S and request devices in D. Since mobile devices are often equipped with a single cellular antenna, each cache device can serve at most one request device, while each request device can only receive from one cache device at one time. That is, φ defines a one-to-one matching between set D and set S.

A cache device is a *potential candidate* for a request device only if it contains the requested message. In addition, each D2D pair should be provided with certain quality of service (QoS) guarantee. We consider a candidate cache device as *feasible* with respect to a request device only if the resulting received SINR is not less than the *decoding threshold* β, which ensures a minimum transmission rate over the D2D link. According to message availability, the sets of cache devices and request devices can be related by a bipartite graph illustrated in Fig. 2, where the left vertices and right vertices are set S and set D, respectively, and each edge indicates that the requested message matches the cached message. If we specify edge weights to the bipartite graph to capture D2D interference and its impact on received SINR, the edge weights are not independent but inter-dependent. This is because, whenever an edge is included in a matching, it causes interference to all matched request devices. Hence, we cannot obtain an optimal device pairing by finding a maximum or minimum weighted bipartite matching, which is solvable in polynomial time.

To characterize the inter-dependency among the edges in Fig. 2, we further structure a 3-uniform hypergraph shown in Fig. 3. Here, the left and right columns of vertices are still set S and set D, respectively, while the middle column of vertices is the set of edges E in the bipartite graph. In this 3-uniform

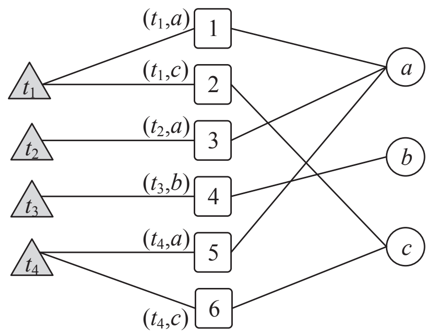

Fig. 3: A 3-uniform hypergraph model for relationship between request devices and cache devices.

hypergraph, each hyperedge consists of one vertex in each of the three sets of vertices, and each hyperedge corresponds to one edge in the bipartite graph. For example, edge (t_2, a) in Fig. 2 is mapped to hyperedge $(t_2, 3, a)$ in Fig. 3, where the middle vertex 3 relabels edge (t_2, a). Notice that each vertex in the middle is only connected to one vertex to the left and one vertex to the right. Therefore, the vertex in the middle can uniquely identify a hyperedge in Fig. 3. To simplify the problem formulation, we add $|D|$ virtual transmitters, where each is dedicated to serve one distinct receiver in D. This extends the hypergraph in Fig. 3 with $|D|$ more vertices on the left, which also result in $|D|$ more hyperedges between the virtual transmitters and the designated receivers. Let S' and E' denote the new sets of transmitters and edges, respectively.

To account for the mutual interference among D2D links, we define two vector variables for each $\ell \in E'$, i.e., $p_\ell = \{p_{\ell,k} : k \in D\}$ and $w_\ell = \{w_{\ell,k} : k \in D\}$, to represent the desired signal and unwanted corresponding interference toward each request device in D, respectively. For example, for edge $\ell = 3 = (t_2, a)$, we have $p_3 = \{s_{t_2,a}, 0, 0\}$ and $w_3 = \{0, s_{t_2,b}, s_{t_2,c}\}$, where $s_{t_2,k} = P_d d_{t_2,k}^{-\alpha} |h_{t_2,k}|^2, k \in \{a, b, c\}$, gives the received power at device k due to the transmission by device t_2. As transmitter t_2 is paired to receiver a, $s_{t_2,a}$ is the desired signal power, while $s_{t_2,b}$ and $s_{t_2,c}$ are the interference caused by transmitter t_2 to device b and c, respectively. For an edge $\ell = (j, k)$ between a virtual transmitter j and receiver k, we have $w_\ell = \{0, ..., 0\}$ and $p_\ell = \{0, ..., s_{j,k}, ..., 0\}$, where $s_{j,k} = \beta \cdot (\sum_{\ell \in E} w_{\ell,k} + w_{c,k} + \sigma^2)$. This implies that a virtual transmitter causes zero interference to others, and the received power at its dedicated receiver is always high enough to achieve an SINR not less than the decoding threshold even if all potential real transmitters in S are selected for transmission. This extension ensures that there always exists a feasible solution that successfully pairs every receiver in D, i.e., the matching between every virtual transmitter to its dedicated receiver. To prioritize the pairing of receivers with real feasible transmitters, we define a cost variable c_ℓ, where $c_\ell = 0$ for each edge that originates from a real cache device and c_ℓ is set to a sufficiently large value Φ otherwise.

Based on the 3-uniform hypergraph model, we can formulate the device pairing problem as (2). Here, y_ℓ can be interpreted as a binary variable indicating whether edge $\ell \in E'$ in the hypergraph is selected for the matching. Each hyperedge is split into two regular edges (j, ℓ) and (ℓ, k) and identified by two binary variables $\phi_{j,\ell}$ and $\psi_{\ell,k}$, which indicate whether there exists an edge between j and ℓ and between ℓ and k, respectively. In addition, $w_{c,k}$ denotes the interference from the cellular user to request device k. By minimizing the total cost, this optimization problem in fact maximizes the pair number associated with real cache devices subject to certain constraints. Constraint (2b) ensures that each cache device is matched to at most one request device, while constraint (2c) requires exactly one (real or virtual) cache device for each request device. Constraint (2d) sets the decoding condition for successful transmission.

$$\text{min.} \quad \sum_{\ell \in E'} y_\ell c_\ell \tag{2a}$$

$$\text{s.t.} \quad \sum_{\ell \in E'} y_\ell \phi_{j,\ell} \leq 1, \forall j \in S' \tag{2b}$$

$$\sum_{\ell \in E'} y_\ell \psi_{\ell,k} = 1, \forall k \in D \tag{2c}$$

$$\sum_{\ell \in E'} y_\ell (\beta w_{\ell,k} - p_{\ell,k}) \leq -\beta(w_{c,k} + \sigma^2), \forall k \in D \tag{2d}$$

$$y_\ell \in \{0, 1\}, \forall \ell \in E'. \tag{2e}$$

III. Efficient Interference-Aware Device Pairing for D2D Communications

As seen in Section II-C, the device pairing problem captures mutual interference among D2D links via two vectors associated with each hyperedge of a 3-uniform hypergraph. An SINR constraint is further incorporated to ensure receiving QoS, but it also increases the computational difficulty. In this section, we introduce an efficient algorithm to derive a near-optimal solution to this problem. Alg. 1 shows the main procedures. First, we apply Lagrangian relaxation to derive an upper bound for the optimal solution. After that, we derive a feasible solution from the upper bound to meet the SINR constraint. Last, we further augment the feasible solution by exploring remaining unpaired devices.

A. Lagrangian Relaxation for Upper Bound

First, we relax the SINR constraint (2d) by Lagrangian relaxation to derive a lower bound for problem (2), which corresponds to an upper bound for the number of matched device pairs. Then, we obtain the following *Lagrangian dual*:

$$\max_{\mu} \quad C(\mu) = \min_{y} \Big[\sum_{\ell \in E'} y_\ell c_\ell + \sum_{k \in D} \mu_k \Big(\sum_{\ell \in E'} y_\ell (\beta w_{\ell,k} - p_{\ell,k}) + \beta(w_{c,k} + \sigma^2) \Big) \Big] \tag{3a}$$

$$\text{s.t.} \quad \sum_{\ell \in E'} y_\ell \phi_{j,\ell} \leq 1, \forall j \in S' \tag{3b}$$

$$\sum_{\ell \in E'} y_\ell \psi_{\ell,k} = 1, \forall k \in D \tag{3c}$$

$$y_\ell \in \{0, 1\}, \forall \ell \in E' \tag{3d}$$

where $\mu = \{\mu_1, ..., \mu_{|D|}\} \geq 0$ are the *Lagrange multipliers*, and $C(\mu)$ is the *Lagrangian subproblem*. As seen, the last term of (3a) is independent of the decision variable y_ℓ given fixed Lagrange multipliers. Essentially, the Lagrangian subproblem is a weighted bipartite matching problem, where each edge ℓ is associated with a weight $(c_\ell + \sum_{k\in D} \mu_k(\beta w_{\ell,k} - p_{\ell,k}))$. Solving the Lagrangian subproblem is to obtain a perfect matching that minimizes the total weight of the matching, which can be achieved by the Kuhn-Munkres algorithm in polynomial time. Then, we can solve the Lagrangian dual in (3) by the subgradient method to iteratively obtain a lower bound closest to the optimum.

B. Derivation of Feasible Solution

The final solution from the above Lagrangian relaxation gives a perfect matching that pairs each request device with a virtual or real cache device. Due to the relaxation, the received SINR at these request devices may not satisfy the minimum decoding threshold. Deriving a feasible solution $\{z_\ell\}$ from the perfect matching $\{\ell : y_\ell = 1 \text{ and } \ell \in E'\}$ is to select a subset of the edges in the matching that originate from a real cache device and end at a request device with a satisfied SINR constraint. Only the edges from E in the matching are considered as candidates, denoted by $\hat{E} = \{\ell : y_\ell = 1 \text{ and } \ell \in E\}$. Correspondingly, let $\hat{D}$ denote the subset of request devices that are matched to real cache devices according to $\hat{E}$. Since a one-to-one matching has been obtained, we have $|\hat{E}| = |\hat{D}|$. Further, the edges in $\hat{E}$ are reordered according to the vertices in $\hat{D}$ for reference convenience. Thus, z_k for $k \in \hat{D}$ refers to the edge in $\hat{E}$ incident on request device k. Moreover, the condition in (2d) can be removed by considering a sufficiently large number Φ as follows:

$$\sum_{\ell\in\hat{E}} z_\ell(\beta w_{\ell,k} - p_{\ell,k}) \leq (1 - z_k)\Phi - z_k\beta(w_{c,k} + \sigma^2), \forall k \in \hat{D}.$$

Thus, the coefficients associated with each edge ℓ toward each receiver device k can be represented by a matrix variable, denoted by $\{\xi_{\ell,k} : \ell \in \hat{E}, k \in \hat{D}\}$ and defined as

$$\xi_{\ell,k} = \begin{cases} \beta w_{\ell,k} - p_{\ell,k}, & \ell \neq k \\ (\beta w_{\ell,k} - p_{\ell,k}) + \beta(w_{c,k} + \sigma^2) + \Phi, & \ell = k. \end{cases}$$

Accordingly, problem (2) is reformulated as

$$\max. \sum_{\ell\in\hat{E}} z_\ell \quad (4a)$$

$$\sum_{\ell\in\hat{E}} z_\ell \xi_{\ell,k} \leq \Phi, \forall k \in \hat{D} \quad (4b)$$

$$z_\ell \in \{0, 1\}, \forall \ell \in \hat{E}. \quad (4c)$$

Based on the above analysis, in Line 12 to Line 22, Alg. 1 processes the upper bound to derive a feasible solution that meets the SINR constraint. As seen, we use a weight parameter δ_k, which evaluates the occupancy of the existing selected edges with respect to each dimension k, i.e., $\delta_k \triangleq \sum_{\ell\in\hat{E}} z_\ell \xi^+_{\ell,k}$. All unselected edges are ranked according to an average size weighted by δ_k. For an unselected edge ℓ,

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Algorithm 1: Augmentation for device pairing.

Input: S, D, E, S', E', $\{p_{\ell,k} : \ell \in E', k \in D\}$, $\{w_{\ell,k} : \ell \in E', k \in D\}$, $\{w_{c,k} : k \in D\}$, $\{\phi_{j,\ell} : j \in S', \ell \in E'\}$, $\{\psi_{\ell,k} : \ell \in E', k \in D\}$, $\{c_\ell : \ell \in E'\}$, σ^2, β, ϵ
Output: $z = \{z_\ell : \ell \in E\}$

1 **begin** Obtain an upper bound y
2   Initialize $\tau \leftarrow 0$, $\mu^\tau \leftarrow \{1, ..., 1\}$, $C^* \leftarrow 0$
3   **repeat**
4   For each edge $\ell \in E'$, define a weight $\rho_\ell = (c_\ell + \sum_{k\in D} \mu_k(\beta w_{\ell,k} - p_{\ell,k}))$
5   Obtain perfect matching y^τ with Kuhn-Munkres
6   Compute value $C(\mu^\tau)$ and subgradient of y^τ
7   **if** $C(\mu^\tau) > C^*$ **then**
8             $y \leftarrow y^\tau, C^* \leftarrow C(\mu_\tau)$
9   Update Lagrange multipliers and step size
10         $\tau \leftarrow \tau + 1$
11   **until** $|C(\mu^\tau) - C(\mu^{\tau-1})| \leq \epsilon$
12 **begin** Derive a feasible matching z
13   Initialize $z_\ell \leftarrow 0, \forall \ell \in \hat{E}$, $\delta_k \leftarrow 1, \forall k \in \hat{D}$
14   Convert coefficients $\xi_{\ell,k}$ to positive $\xi^+_{\ell,k}, \forall k \in \hat{D}$
15   **repeat**
16   Sort unselected edges in $\hat{E}$ to $\hat{\mathbb{E}}$ in ascending order of weighted average size: $\sum_{k\in\hat{D}} \delta_k \cdot \xi^+_{\ell,k}$
17   **foreach** $\ell \in \hat{\mathbb{E}}$ **do**
18   **if** *Capacity constraint (4b) is satisfied* **then**
19   Set $z_\ell \leftarrow 1$ and update $\hat{E} \leftarrow \hat{E} \setminus \ell$
20   Update occupancy, weighted average size, unpaired device sets $\bar{S}$ and $\bar{D}$
21   Break
22   **until** *No feasible edge to add*
23 **begin** Enhance the feasible matching z
24   Obtain candidate cache devices $\bar{S}_k$ from $\bar{S}$, $\forall k \in \bar{D}$
25   *stop* $\leftarrow 0$
26   **repeat**
27   Sort $\bar{D}$ to $\bar{\mathbb{D}}$ according to ascending order of $|\bar{S}_k|$
28   **foreach** $k \in \bar{\mathbb{D}}$ **do**
29   Sort cache devices in $\bar{S}_k$ to $\bar{\mathbb{S}}_k$ in ascending order of total interference to existing pairs
30             $cacheFound \leftarrow 0$
31   **foreach** $j \in \bar{\mathbb{S}}_k$ **do**
32   **if** *Capacity constraint (4b) is satisfied after adding pair* (j, k) **then**
33   Set $z_\ell \leftarrow 1$, for $\ell = (j, k)$
34   Update $\bar{S}$, $\bar{D}$, and $\bar{S}_k$ with j
35                     $cacheFound \leftarrow 1$ and Break
36   **if** $cacheFound = 1$ **then** Break
37   **else** *stop* $\leftarrow 1$
38   **until** *stop* $= 1$
39 Return z

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its average size is defined as $\sum_k \delta_k \cdot \xi^+_{\ell,k}$. This definition of average size is based on the greedy ranking metric proposed by Toyoda for the multidimensional knapsack problem (MDKP) [6]. The average size captures the overall demand of an unselected edge. Because a higher occupancy implies a more consumed dimension, an edge with a larger demand in that dimension should be ranked lower. Thus, according to an ascending order of the average size of the unselected edges, each edge is checked whether it meets the capacity constraint (4b) if selected. The first satisfied edge is selected and the ranking of remaining unselected edges is updated accordingly. At the beginning, as the initial solution $z_\ell = 0, \forall \ell \in \hat{E}$, we set all $\delta_k = 1$. Thus, in the first iteration, the edge with the minimum total size $\min_\ell \sum_k \xi^+_{\ell,k}$ is selected if constraint (4b) is satisfied. This procedure continues until every candidate edge is selected or no more feasible edge can be added.

C. Further Augmentation

After deriving a feasible matching solution, $\{\ell : z_\ell = 1 \text{ and } \ell \in \hat{E}\}$, Alg. 1 further augments it in Line 23 to Line 38 by adding more feasible pairs from the unpaired request devices. Let $\bar{D}$ and $\bar{S}$ denote the unpaired request devices and unpaired cache devices, respectively. The candidate cache devices $\bar{S}_k$ is first obtained for each request device $k \in \bar{D}$. Then, the request devices in $\bar{D}$ are sorted according to an ascending order of the number of candidate cache devices. That is, a request device with the fewest candidate cache devices is considered first as other request devices have more options. For each request device, its candidate cache devices are also ranked in a specific order. For request device k, each of its candidate cache devices $j \in \bar{S}_k$ is evaluated according to the total interference to existing device pairs, i.e., $\sum_{k' \in D \setminus \bar{D}} w_{\ell,k'}$, where edge $\ell = (j,k)$ is from cache device j to request device k. The cache device that will cause the lowest interference is considered in priority. Then, request device $k \in \bar{D}$ is paired to a feasible candidate cache device in $\bar{S}_k$ if the new pair will satisfy the SINR constraint and will not cause any SINR violation to existing device pairs. The above procedure keeps iterating until no feasible request device and cache device can be paired. As seen, through this enhancement procedure, we can not only add more feasible device pairs, but also restrict the interference impact in the mean time.

IV. Numerical Results and Discussions

To evaluate the performance of our proposed algorithms, we conduct computer simulations with a circular region of a radius 500m, in which the BS is located at the center point, and request devices and cache devices are uniformly distributed within the area. The cache devices reuse the uplink of a cellular user which is uniformly distributed within the circular region. The transmit powers of D2D transmitters and cellular user are set to 100mW. The requests from the request devices follow a Zipf distribution of an exponent $\gamma_r = 0.9$ toward a set of messages. The cache devices store the messages in the set according to a Zipf distribution of the same exponent $\gamma_c = 0.9$ [7]. The path-loss exponent and noise variance are set to $\alpha = 4$ and $\sigma^2 = 5 \times 10^{-10}$, respectively.

In addition to our proposed algorithm, we consider three reference schemes for the D2D device pairing problem:

- The optimal solution – The device pairing problem in (2) can be solved by the GNU Linear Programming Kit (GLPK) package when the problem size is small.
- A heuristic channel-aware scheme – Based on the approach proposed in [5], the request devices are considered one by one according to certain order. Each request device under consideration is paired to the feasible cache device that achieves the highest data rate while not violating the SINR constraint for already paired request devices.
- A swap-matching scheme – This is inspired by the user-subcarrier swap-matching algorithm (USMA) proposed in [8] for radio resource allocation. This scheme first constructs an initial matching by iteratively selecting an arbitrary unmatched request device and pairing it with a feasible cache device randomly. Then, each matched request device keeps searching for a new request device for swapping until a stable matching is formed.

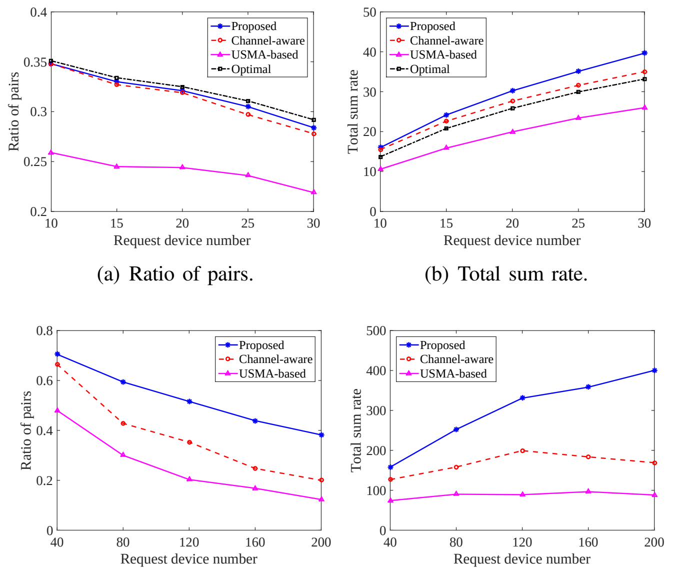
A. Effect of Number of Request Devices

In this subsection, we evaluate the performance of the proposed approach and the reference schemes when the number of request devices varies. Fig. 4 shows the ratio of the number of matched pairs to the number of request devices, as well as the total sum rate per Hz. First, we fix the number of cache devices to 30 and increase the number of request devices from 10 to 30. The results are based on the average of 100 runs. As seen, the performance of our approach is fairly close to that of the optimal solution and the gap between our approach and the channel-aware scheme becomes slightly larger when there are more request devices. In addition, the ratio of pairs decreases with an increasing number of request devices, although we find that the number of matched pairs increases in the meantime.

Furthermore, in Fig. 4(c) and Fig. 4(d), we increase the network scale so that there are 200 cache devices and the number of request devices increases from 40 to 200. When the network scale becomes large, it is extremely difficult to obtain the optimal solution. Hence, we only compare our approach with the channel-aware scheme and the USMA-based scheme in the large-scale networks. As seen, the gap between our approach and the reference schemes becomes more significant. Similar to Fig. 4(b), Fig. 4(d) shows that our approach achieves the highest sum rate and it grows rapidly with the number of request devices. Though the channel-aware scheme tends to match pairs with high achievable data rates, the heuristic nature limits its overall performance. The USMA-based scheme uses a swapping procedure, but its matching result is not so optimized as the one obtained by Alg. 1.

B. Effect of Number of Cache Devices

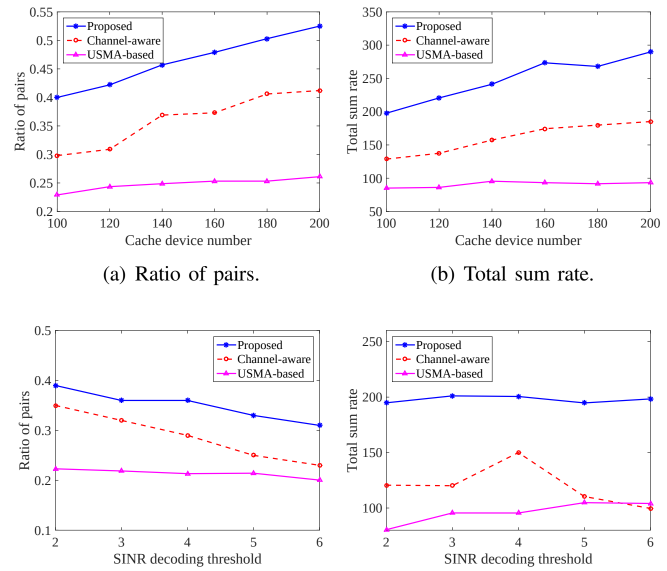
In this subsection, we evaluate the effect of cache devices on the pairing performance. For space limitation, we only include the results for the large-scale networks, where there are 100



(a) Ratio of pairs. (b) Total sum rate.

(c) Ratio of pairs. (d) Total sum rate.

Fig. 4: Performance with a different number of request devices.



(a) Ratio of pairs. (b) Total sum rate.

(c) Ratio of pairs. (d) Total sum rate.

Fig. 5: Performance with a different number of cache devices and SINR decoding threshold in large-scale networks.

request devices and the number of cache devices is varied between 100 and 200. As seen in Fig. 5(a), when there are more cache devices available in the network, more request devices are successfully paired. Correspondingly, Fig. 5(b) shows that these D2D pairs achieve higher sum rates. This can be interpreted easily since a larger number of cache devices offer more available resources in caching capacities and communication spectrum to fulfill more requests.

C. *Effect of SINR Decoding Threshold*

Last we examine the effect of SINR decoding threshold β. Here, the numbers of request devices and cache devices are both set to 100. When the SINR decoding threshold increases from 2 to 6, Fig. 5(c) and Fig. 5(d) show the corresponding performance. Consistently, it is observed that our proposed approach performs the best with different SINR thresholds. We also notice that the ratio of matched pairs in all three schemes slowly decreases with SINR threshold. This is obvious since a higher decoding threshold improves the QoS requirement for candidate cache devices, and thus reduces the number of potential device pairs. As a result, fewer devices are successfully matched and lead to a lower pairing ratio. In Fig. 5(d), the fluctuation and slight increase of sum rate with the decoding threshold is due to the trade-off between each pair's achievable data rate and the number of pairs restricted by the overall interference. Although a larger SINR threshold ensures a higher data rate for each pair, fewer pairs can be potentially available and negatively affect the total sum rate.

V. Conclusion

In this paper, we investigate the device pairing problem for collaborative data dissemination with D2D communications. The problem aims to optimize the pairing between request devices and cache devices, so that the available spectrum and storage resources are utilized efficiently to serve message requests. This problem is formulated as an integer optimization problem over a 3-uniform hypergraph with inter-dependent edge weights. The SINR constraint to ensure receiving QoS at request devices further complicates the solution. To address the computational challenge, we propose an efficient interference-aware approximation algorithm that derives a near-optimal device pairing. The simulation results show that our approach performs fairly closely to the optimal solution in a small-scale network. In a large-scale network, significant performance gain is achieved over two existing schemes.

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