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Stable Device Pairing for Collaborative Data Dissemination with Device-to-Device Communications

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***Abstract*—With the rapid expansion of Internet-of-Things (IoT), tremendous traffic produced by a vast number of IoT devices is being injected into networks and straining their capacity. To address the challenge, device-to-device (D2D) communications offer a promising technique that relieves network overloading by localizing traffic between devices. In this paper, we investigate how to exploit D2D communications to support data dissemination and offload traffic. In particular, we focus on an important problem that aims to effectively pair request devices with cache devices in close proximity. Due to the interference among D2D links, we prove that this device pairing problem is NP-hard and thus requires an approximation algorithm to solve it efficiently. Here, we propose a three-step approach, in which the first step uses Lagrangian relaxation to obtain an upper bound solution, the second step derives a feasible solution from the initial pairing and further augments it, and the last step uses a swapping algorithm to refine the pairing to guarantee its stability. The proposed approach is proved to converge to a two-sided exchange stable matching. Extensive simulation results show that our three-step approach performs closely to the optimal solution and achieves significant performance gain over the existing schemes.**

***Index Terms*—Internet-of-Things, D2D communications, collaborative data dissemination, device pairing, stable matching.**

I. Introduction

Driven by the proliferation of smart devices and evolution of mobile networks, it is expected that billions of Internet-of-Things (IoT) devices will be connected to offer ubiquitous access to any content on any device from anywhere. The vast number of IoT devices and their resulting traffic will further stress the network infrastructure, which is already being strained by the rapid growth of mobile data. To accommodate the surging demands, device-to-device (D2D) communications provide an effective technique that enables mobile devices to directly communicate with each other bypassing base stations (BSs). Exploiting the close proximity, D2D communications offer various benefits such as high data rates, energy saving, coverage expanding, and traffic offloading. Many studies on D2D communications concern key issues such as resource allocation and medium access control [1,2].

Meanwhile, the network is migrating to an information-centric paradigm and becomes dominated by information dissemination rather than end-to-end communications. For example, an important service of vehicular networks is to disseminate emergency messages or popular contents toward target vehicles [3]. The resource-rich end devices at the network edge (e.g., smartphones, tablets, and vehicles) can behave like fog nodes to facilitate cost-effective data dissemination [4]. In the literature, there have been some existing works on data dissemination that leverages vehicle-to-vehicle (V2V) relay [5,6] or D2D communications [7]–[9]. Many studies focus on multi-hop message forwarding to ensure sufficient user coverage while minimizing dissemination latency or maximizing delivery ratio. Some works also explore how to place available content items in caching devices so as to serve as many request users as possible [6,8]. When D2D communications are involved in data dissemination, another important problem is the pairing of request devices with cache devices. In the literature, it is often assumed for simplicity that a cache device can serve an arbitrary request device within a collaboration distance. However, this may cause intolerable interference and thus cannot achieve the full potential of D2D communications in data dissemination. Furthermore, considering the independent interests of cache devices and request devices, it is crucial to guarantee the stability of the pairing result.

Based on these considerations, in this paper, we study stable device pairing for collaborative data dissemination with D2D communications. The device pairing problem is formulated as an NP-hard integer program. It can also be transformed into a one-to-one matching problem with externality. To address the computational intractability, we propose a three-step approach, in which the first two steps determine as many device pairs as possible and the third step amends the pairing result to ensure stability. Specifically, the first step uses Lagrangian relaxation to obtain an upper bound solution for the device pairing problem. Then, the second step derives a feasible solution from the initial result of the first step and further augments it by exploring remaining unpaired devices. Last, the third step uses a swapping algorithm to refine the pairing result to guarantee convergence to a two-sided exchange stable matching. Thus, both request devices and cache devices are willing to accept the pairing result since there is no possible swap that strictly increases the utility of at least one involved

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device while not decreasing any device's utility.

Specifically, the major contributions of this paper are several-fold as follows:

- We explore the problem of pairing request devices with cache devices for collaborative data dissemination assisted with D2D communications. We analyze and formulate this problem as an integer linear program. Furthermore, we prove that this device pairing problem is NP-complete in its decision form and thus NP-hard in the optimization form.
- To address the computational intractability, we propose a near-optimal and stable three-step solution. The proposed solution consists of a Lagrangian relaxation based algorithm, an augmentation algorithm, and a swapping algorithm. Particularly, we prove that the pairing result is two-sided exchange stable.
- We conduct extensive simulations to evaluate the performance of our proposed approach in different aspects. The simulation results show that the three-step approach can significantly improve the efficiency of D2D-assisted data dissemination, and it achieves high performance fairly close to that of the optimal solution.

The remainder of this paper is organized as follows. In Section II, we review related works on data dissemination and the use of matching with externality in wireless networks. Section III gives the system model for data dissemination and D2D channel. Section IV formulates the device pairing problem and analyzes its computational hardness. In Section V, we present the proposed three-step approach to solve the device pairing problem. In Section VI, we evaluate the performance of the proposed approach and compare it with existing solutions. Section VII concludes this research work.

II. Related Work

In the literature, there have been some existing works on data dissemination over vehicular networks. In [5], a multi-hop broadcast solution is proposed for emergency message dissemination in vehicular ad hoc networks. The proposed solution includes a novel forwarding node selection scheme that utilizes iterative partition, mini-slot, and black-burst to quickly select remote neighbouring nodes and choose a single forwarding node by asynchronous contention among them. The work in [10] also studies dissemination of time-critical messages over intermittently connected mobile networks. A relaying scheme termed Last-Create-First-Relay (LC-FR) is analyzed under the 1-hop or 2-hop mode with respect to message delivery ratio and average delay. In [6], Luan *et al.* further consider prefetching contents to roadside buffers to facilitate content dissemination to vehicles in the urban area. A fully distributed content replication scheme is designed to optimize global network utility that accounts for both user experience and download demands.

In addition to the specialized vehicular environment, there are many works on D2D-assisted data dissemination. In [11], Chen *et al.* study a D2D content distribution scenario, in which a helper user can transmit data to another user requesting the file within a *collaboration distance*. They consider a user-centric proactive caching strategy to maximize the offloaded traffic. Also, they optimize the transmission power of D2D transmitters to minimize their energy consumption. In [12], 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. The work in [13] considers a more realistic interference-aware D2D channel model and studies the pairing of request devices and cache devices for collaborative content distribution. The D2D pairing problem is formulated as an integer linear program and solved by a heuristic channel-aware algorithm.

As this work involves a matching problem with externality, the following reviews some related works in this area. For example, many-to-one matching with externality has been utilized to study user-cell association [14] and spectrum sharing in wireless networks [15]. In [14], Pantisano *et al.* investigate user-cell association in wireless small cell networks by exploiting context information extracted from users' devices. A distributed algorithm is proposed to form a stable matching that guarantees applications' quality of service (QoS) requirements. In [15], spectrum sharing among multiple operators is studied for an indoor deployment scenario. A Markov chain Monte Carlo (MCMC) based algorithm is used to obtain a stable matching that assigns resource blocks to operators. In [16], Di *et al.* study radio resource allocation for an uplink sparse code multiple access network, focusing on subcarrier assignment and power allocation. This problem is modelled as many-to-many matching with externality and solved by a swapping algorithm that begins with a random feasible matching and iteratively searches for a final stable matching.

III. System Model

A. Data Dissemination Scenario

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 BS centered at the origin. Each device $k \in D$ requests one message from set M independently according to a popularity distribution. In addition, there are another set of devices, S, which are randomly distributed within the cell coverage. Considering the random caching policy studied in [12], we assume that each device $j \in S$ caches at most m_c messages from set M. 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. The BS can use a dedicated wireless control channel to collect information on the demands of request devices, caching information of cache devices, and channel states of potential D2D links. Then, the BS determines the pairing between cache devices in S and request devices in D. Last, the BS sends the pairing result to the relevant devices via the control channel, and inform them of the D2D data channel

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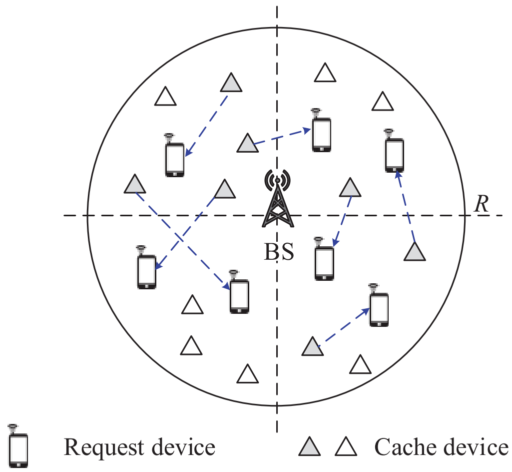

Fig. 1: Device pairing for D2D-assisted data dissemination.

for the cache devices to deliver the requested contents. This D2D-assisted data dissemination not only can offload traffic from the BS but also can reduce energy consumption with the close proximity.

B. D2D Channel Model

Here, we consider a D2D underlaid cellular network, where the D2D links share the uplink spectrum of regular cellular users. It is assumed 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. There are several reasons for favoring the use of uplink resources, since the uplink resources are often less utilized, and the BS is more powerful in interference mitigation [17]. Nonetheless, when a larger number of D2D transmitters are active simultaneously, the interference to the cellular user may be non-negligible. Hence, the BS should apply advanced resource allocation to assign an uplink channel for the D2D users so that uplink interference is mitigated and the QoS of the interfered cellular user is assured [18]–[20].

To offload message requests from the BS, a request device can be paired to a feasible cache device that delivers the message content via D2D communications. 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 written as

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

In (1), 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 transmitted 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.

As seen in (1), the received signal at D2D receiver k includes the desired 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

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

For given a carrier bandwidth B, the maximum achievable data rate at request device k can be obtained as

$$r_k = B \cdot \log_2(1 + \Gamma_k). \tag{3}$$

C. Device Pairing Problem

Considering the D2D-assisted data dissemination scenario depicted in Fig. 1, 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.

For each device pair, the cache device must store the message demanded by the request device. In addition, each D2D pair should be provided with certain QoS guarantee. Here, we require that the received SINR at the D2D receiver should not be less than a *decoding threshold* β, which ensures a minimum transmission rate over the D2D link. Hence, we need to consider the message availability as well as the mutual interference among D2D links to determine a device pairing result. A desirable pairing result is expected to optimize the spatial distributions of D2D transmitters and receivers so that a maximum number of request devices are served with satisfactory SINR.

For this device pairing problem, the overall system goal can conflict with a device's individual interest, e.g., with respect to the transmission rate. It is possible that a request device is not matched to its preferred cache device so that other requests are fulfilled. As a consequence, the pairing assignment may be declined and cause system instability. Hence, a stable pairing result is desired such that a device's individual utility is accommodated while maintaining high system-level performance.

IV. Analysis of Device Pairing Problem

A. Problem Formulation

As defined in Section III-C, a cache device is a *potential candidate* for a request device only if it contains the requested message. This relationship is modelled by a bipartite graph as 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.

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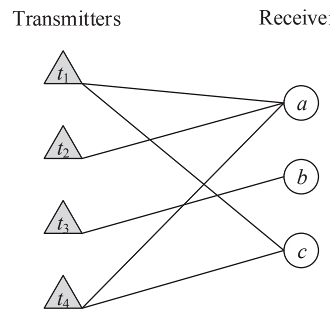

Fig. 2: A bipartite graph model for relationship between cache devices and request devices.

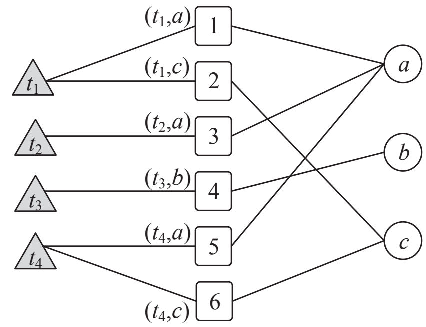

Fig. 3: A 3-uniform hypergraph model for relationship between cache devices and request devices.

Based on the bipartite graph, the device pairing problem is to obtain a maximum one-to-one matching subject to certain QoS constraint. A candidate cache device is *feasible* with respect to a request device only if the resulting received SINR is not less than the decoding threshold. If we further specify edge weights for the bipartite graph to capture D2D interference and its impact on received SINR, the edge weights are not independent as in regular bipartite graphs but inter-dependent in our case. 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 capture the mutual interference among D2D links and inter-dependency among edges, we view these edges as another set of vertices and structure a 3-uniform hypergraph as shown in Fig. 3. The left column of vertices is set S, the right column of vertices is set D, while the middle column of vertices is the set of edges E in the bipartite graph. In this 3-uniform 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) between vertices t_2 and a in Fig. 2 is mapped to hyperedge $(t_2, 3, a)$ in Fig. 3, where the first vertex $t_2 \in S$, the middle vertex 3 relabels edge (t_2, a), and the last vertex $a \in D$. For reference convenience in the following, we use a binary variable, e^{ℓ}_{jk}, to indicate whether there exists a hyperedge (j, ℓ, k) in the 3-uniform hypergraph, which also indicates whether there is a regular edge, $\ell = (j, k) \in E$, from vertex $j \in S$ toward vertex $k \in D$ in the bipartite graph.

As discussed above, the selection of an edge in the bipartite graph results in both the desired signal toward an intended request device and unwanted interference signals to other D2D receivers. After transforming the bipartite graph into the 3-uniform hypergraph, we can see that the middle vertex of each hyperedge is connected to only one vertex to the left and one vertex to the right. Therefore, the vertex in the middle can uniquely identify a hyperedge in the hypergraph. Then, to capture the mutual interference among D2D links, the impact of each edge in the bipartite graph can be characterized by some weights with respect to the middle vertex of the corresponding hyperedge. Specifically, 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 corresponding unwanted interference signal 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 $s_{t_2,k} = P_d d^{-\alpha}_{t_2,k} |h_{t_2,k}|^2, k \in \{a, b, c\}$, 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. In fact, there is only one non-zero value in each vector p_ℓ for the intended receiver device, while the corresponding value in w_ℓ is the only zero value in the vector to indicate that it is not the interference but the desired signal. All non-zero values in p_ℓ and w_ℓ give the received power at all request devices in D. Since each edge ℓ represents one potential D2D pair, we need to use two vectors p_ℓ and w_ℓ to distinguish the desired signal from the unwanted interference for this D2D pair.

Based on the 3-uniform hypergraph model, we can formulate the device pairing problem as (4). Here, $x_{j,k}$ is a binary variable that indicates whether cache device $j \in S$ is matched to serve request device $k \in D$. In addition, $w_{c,k}$ denotes the interference from the cellular user to request device k. This optimization problem aims to maximize the total number of device pairs subject to three constraints. Constraints (4b) and (4c) ensure that each cache device is matched to at most one request device and vice versa. Constraint (4d) requires that each paired receiver k should meet the decoding condition for successful transmission. The last constraint (4e) limits $x_{j,k}$ to be integer 0 or 1.

$$\max_{x} \quad \sum_{j \in S} \sum_{k \in D} x_{j,k} \tag{4a}$$

$$\text{s.t.} \quad \sum_{k \in D} \sum_{\ell \in E} x_{j,k} e^{\ell}_{j,k} \leq 1, \forall j \in S \tag{4b}$$

$$\sum_{j \in S} \sum_{\ell \in E} x_{j,k} e^{\ell}_{j,k} \leq 1, \forall k \in D \tag{4c}$$

$$\frac{\sum_{j \in S} \sum_{\ell \in E} x_{j,k} e^{\ell}_{j,k} p_{\ell,k}}{\sum_{j \in S} \sum_{\ell \in E} \left(\sum_{k' \in D} x_{j,k'} \right) e^{\ell}_{j,k} w_{\ell,k} + w_{c,k} + \sigma^2} \geq \beta, \tag{4d}$$

$$\forall \sum_{j \in S} x_{j,k} = 1, k \in D$$

$$x_{j,k} \in \{0, 1\}, \forall j \in S, k \in D. \tag{4e}$$

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Note that constraint (4d) is defined only for the receivers that are successfully paired. To remove this condition and simplify the formulation, we add $|D|$ virtual transmitters, each of which 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. For any new edge $\ell = (j,k)$ between 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. Accordingly, problem (4) can be modified to the following problem (5):

$$\min_{x} \quad \sum_{j\in S'}\sum_{k\in D} x_{j,k}c_{j,k} \tag{5a}$$

$$\text{s.t.} \quad \sum_{k\in D}\sum_{\ell\in E'} x_{j,k}e^{\ell}_{j,k} \le 1, \forall j \in S' \tag{5b}$$

$$\sum_{j\in S'}\sum_{\ell\in E'} x_{j,k}e^{\ell}_{j,k} = 1, \forall k \in D \tag{5c}$$

$$\frac{\sum_{j\in S'}\sum_{\ell\in E'} x_{j,k}e^{\ell}_{j,k}p_{\ell,k}}{\sum_{j\in S'}\sum_{\ell\in E'}\left(\sum_{k'\in D} x_{j,k'}\right)e^{\ell}_{j,k}w_{\ell,k} + w_{c,k} + \sigma^2} \ge \beta, \tag{5d}$$

$$\forall k \in D$$

$$x_{j,k} \in \{0,1\}, \forall j \in S', k \in D. \tag{5e}$$

Due to the extension with virtual transmitters, the objective function value for problem (4) becomes $|D|$. To prioritize the pairing of receivers with real feasible transmitters in problem (5), we define cost variable $c_{j,k}$, where $c_{j,k} = 0$ for each edge that originates from a real cache device and $c_{j,k}$ is set to a sufficiently large value Φ otherwise. As seen, the objective function (5a) further involves the cost variable $c_{j,k}$, constraint (5c) replaces the inequality in (4c) by equality, and constraint (5d) converts the conditional constraint in (4d) into an unconditional one.

Further simplifying the notation in (5), we can rewrite the device pairing problem as

$$\min_{y} \quad \sum_{\ell\in E'} y_\ell c_\ell \tag{6a}$$

$$\text{s.t.} \quad \sum_{\ell\in E'} y_\ell \phi_{j,\ell} \le 1, \forall j \in S' \tag{6b}$$

$$\sum_{\ell\in E'} y_\ell \psi_{\ell,k} = 1, \forall k \in D \tag{6c}$$

$$\sum_{\ell\in E'} y_\ell(\beta w_{\ell,k} - p_{\ell,k}) \le -\beta(w_{c,k} + \sigma^2), \forall k \in D \tag{6d}$$

$$y_\ell \in \{0,1\}, \forall \ell \in E'. \tag{6e}$$

Here, y_ℓ can be interpreted as a binary variable indicating whether edge ℓ in the hypergraph is selected for the matching. Previously, we use $e^{\ell}_{j,k}$ to define the existence of a hyperedge with three vertices (j,ℓ,k). For notation simplicity, we split a hyperedge into two regular edges (j,ℓ) and (ℓ,k) and use binary variables $\phi_{j,\ell}$ and $\psi_{\ell,k}$ to indicate whether there exists an edge between j and ℓ and between ℓ and k, respectively. Since two vertices (j,k) uniquely identify hyperedge ℓ, we rewrite $c_{j,k}$ as c_ℓ. Constraints (6b) and (6c) are the one-to-one matching constraints, which ensure that there always exists a feasible solution that pairs every request device to a real or virtual cache device. The SINR constraint in (6d) is similar to (4d) and (5d).

B. Problem Hardness

Section IV-A gives several equivalent formulations of the device pairing problem, which is computationally hard. In this section, we prove that the decision form of this problem is NP-complete, i.e., its optimization form in (6) is NP-hard.

Lemma 1. *The device pairing problem in (6) is NP.*

Proof. Consider the decision form of (6): Does there exist a perfect matching that satisfies the SINR constraint (6d) and has a cardinality not less than a given value?

Given a solution $\{y_\ell\}$ as the input to problem (6), it takes time $O(|S|\cdot|D|)$ to verify each constraint (including the SINR constraint) and find a true or false answer to the above decision problem. Therefore, the device pairing problem in (6) is NP. □

Theorem 1. *The device pairing problem in (6) is NP-complete.*

Proof. According to Lemma 1, the device pairing problem in (6) is NP. To prove problem (6) is NP-complete, we will reduce a known NP-complete problem to an instance of (6).

Consider an instance of the hypergragh in Fig. 3 where only one edge is incident on each vertex in S. Then, constraint (6b) is redundant. Rewriting the coefficients in (6d) as general parameters, we formulate this special case of problem (6) as

$$\max_{y} \quad \sum_{\ell\in E'} y_\ell v_\ell \tag{7a}$$

$$\sum_{\ell\in E'} y_\ell \psi_{\ell,k} = 1, \forall k \in D \tag{7b}$$

$$\sum_{\ell\in E'} y_\ell \omega_{\ell,k} \le b_k, \forall k \in D \tag{7c}$$

$$y_\ell \in \{0,1\}, \forall \ell \in E'. \tag{7d}$$

Next, we show that the NP-complete *partitioning problem* can be reduced to an instance of problem (7). The decision form of the partitioning problem is stated as follows: Given a set of n numbers, $Y = \{a_i, i = 1,...,n\}$, decide whether Y can be partitioned into two subsets Y_1 and Y_2 such that $\sum_{a_i\in Y_1} a_i = \sum_{a_i\in Y_2} a_i = A/2$, where $A = \sum_{a_i\in Y} a_i$.

Corresponding to the partitioning problem, we create an instance of problem (7) with $2n$ decision variables $\{y_1,...,y_{2n}\}$ and $v_\ell = 1$ for $1 \le \ell \le 2n$. Here, the n decision variables of odd indices, $\{y_1, y_3, y_5, ...\}$, indicate whether the n numbers in Y are selected for subset Y_1. Similarly, the other n decision variables of even indices, $\{y_2, y_4, y_6, ...\}$, define the membership of the n numbers in Y for subset Y_2. In addition, we use constraint $\sum_\ell y_\ell \psi_{\ell,k} = 1, \forall 1 \le k \le n$, to restrict that each number in Y is only allocated to one of the two subsets. Then, $\psi_{\ell,k}$ is written as the following $2n \times n$ matrix

$$\{\psi_{\ell,k}\} = \begin{bmatrix} 1 & 0 & 0 & 0 & \dots & 0 & 0 \\ 1 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & 1 & 0 & 0 & \dots & 0 & 0 \\ 0 & 1 & 0 & 0 & \dots & 0 & 0 \\ & & \dots & \dots & \dots & & \\ 0 & 0 & 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & 0 & 0 & \dots & 0 & 1 \end{bmatrix}.$$

Last, the two conditions in the partitioning problem, $\sum_{a_i \in Y_1} a_i = \sum_{a_i \in Y_2} a_i = A/2$, can be translated into two knapsack-like capacity constraints by defining $b_1 = b_2 = A/2$ and $b_k = 0$ for any $3 \le k \le n$. Accordingly, the weight coefficients $\omega_{\ell,k}$ are written as the following $2n \times n$ matrix

$$\{\omega_{\ell,k}\} = \begin{bmatrix} a_1 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & a_1 & 0 & 0 & \dots & 0 & 0 \\ a_2 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & a_2 & 0 & 0 & \dots & 0 & 0 \\ & & \dots & \dots & \dots & & \\ a_n & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & a_n & 0 & 0 & \dots & 0 & 0 \end{bmatrix}.$$

As the weights with respect to all dimensions except for the first two are all zeros, the capacity constraints for these dimensions are always satisfied. The capacity constraints for the first two dimensions essentially limit that the sum of the numbers in either subset is not greater than $A/2$. Since the total sum of all numbers is A, the sum of each subset is $A/2$ when both capacity constraints are satisfied.

For the created instance of problem (7), if there exists a feasible solution that gives an objective value $\sum_\ell y_\ell v_\ell = n$, the answer is *yes* to the decision form of the partitioning problem. Conversely, the answer is *no*. Thus, it is proved that the partitioning problem is reduced to problem (7). Since the partitioning problem is NP-complete, the decision form of problem (7) is also NP-complete. As problem (6) generalizes (7), the device pairing problem (6) is also NP-complete. □

V. Stable Solution to Device Pairing Problem

As analyzed, the device pairing problem is NP-complete. To address the computational intractability, we propose a three-step approach. First, we apply Lagrangian relaxation to derive an upper bound for the optimal solution. After that, we develop an augmentation algorithm that obtains a feasible solution from the upper bound and further enhances it to a near-optimal solution. Last, we design a swapping algorithm to accommodate the individual device's utility concern and ensure stability for the pairing result.

A. Derivation of Upper Bound

As seen in problem (6), the SINR constraint (6d) is hard. Therefore, we relax this constraint by Lagrangian relaxation to derive a lower bound for problem (6), which corresponds to an upper bound for the original device pairing problem in (4). Alg. 1 shows the details of the procedure.

Algorithm 1: An upper bound for device pairing by Lagrangian relaxation and subgradient.

```
Input: S', D, E', {p_{ℓ,k} : ℓ ∈ E', k ∈ D},
       {w_{ℓ,k} : ℓ ∈ E', k ∈ D}, {w_{c,k} : k ∈ D},
       {φ_{j,ℓ} : j ∈ S', ℓ ∈ E'}, {ψ_{ℓ,k} : ℓ ∈ E', k ∈ D},
       {c_ℓ : ℓ ∈ E'}, σ^2, β, ϵ
Output: y = {y_ℓ : ℓ ∈ E'}
Initialize τ ← 0, ζ^τ ← 1, μ^τ ← {1, ..., 1}, C* ← 0
repeat
    For each edge ℓ ∈ E', define a weight
      ρ_ℓ = (c_ℓ + Σ_{k∈D} μ_k (β w_{ℓ,k} − p_{ℓ,k}))
    Use Kuhn-Munkres algorithm to obtain a perfect
      matching y^τ of minimum total weight
    Compute objective value with the perfect matching:
      C(μ^τ) ← Σ_{ℓ∈E'} y^τ_ℓ ρ_ℓ + Σ_{k∈D} μ_k β(w_{c,k} + σ^2)
    Compute subgradient:
      g^τ_k = Σ_{ℓ∈E'} y^τ_ℓ (β w_{ℓ,k} − p_{ℓ,k}) + β(w_{c,k} + σ^2), ∀k ∈ D
    if C(μ^τ) > C* then
        y ← y^τ, C* ← C(μ_τ)
    Update Lagrange multipliers:
      μ^{τ+1} ← max{0, μ^τ + ζ_τ g^τ}
    Update step size: ζ_{τ+1} ← ζ_τ/2
    τ ← τ + 1
until |C(μ^τ) − C(μ^{τ−1})| ≤ ϵ
Return y
```

Relaxing constraint (6d), we have the *Lagrangian dual*:

$$\max_{\mu} \; C(\mu) = \min_{y} \Big[\sum_{\ell \in E'} y_\ell c_\ell + \sum_{k \in D} \mu_k \Big(\sum_{\ell \in E'} y_\ell (\beta w_{\ell,k} - p_{\ell,k}) + \beta (w_{c,k} + \sigma^2) \Big) \Big] \tag{8a}$$

$$\text{s.t.} \quad \sum_{\ell \in E'} y_\ell \phi_{j,\ell} \le 1, \forall j \in S' \tag{8b}$$

$$\sum_{\ell \in E'} y_\ell \psi_{\ell,k} = 1, \forall k \in D \tag{8c}$$

$$y_\ell \in \{0,1\}, \forall \ell \in E' \tag{8d}$$

where $\mu = \{\mu_1, ..., \mu_{|D|}\} \ge 0$ are the *Lagrange multipliers*, and $C(\mu)$ is the *Lagrangian subproblem*, given by

$$\min_{y} \; \sum_{\ell \in E'} y_\ell \Big(c_\ell + \sum_{k \in D} \mu_k (\beta w_{\ell,k} - p_{\ell,k}) \Big) + \sum_{k \in D} \mu_k \beta (w_{c,k} + \sigma^2) \tag{9a}$$

$$\text{s.t.} \quad \sum_{\ell \in E'} y_\ell \phi_{j,\ell} \le 1, \forall j \in S' \tag{9b}$$

$$\sum_{\ell \in E'} y_\ell \psi_{\ell,k} = 1, \forall k \in D \tag{9c}$$

$$y_\ell \in \{0,1\}, \forall \ell \in E'. \tag{9d}$$

As seen in objective function (9a), the last term 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.

To solve the Lagrangian dual in (8), we can use the subgradient method to iteratively obtain a lower bound closest to the optimum. Let μ^τ denote the tentative solution to the Lagrangian dual in iteration τ. According to the subgradient method, μ^τ is updated at the end of iteration τ to

$$\mu^{\tau+1} = \max\{0, \mu^\tau + \zeta_\tau g^\tau\} \tag{10}$$

where ζ_τ is the step size and $g^\tau = \{g_k^\tau : \forall k \in D\}$ is the subgradient in iteration τ. Let y^τ denote the solution to the Lagrangian subproblem in iteration τ. The subgradient of $C(\mu)$ with respect to the kth Lagrange multiplier μ_k is given by

$$g_k^\tau = \sum_{\ell\in E'} y_\ell^\tau(\beta w_{\ell,k} - p_{\ell,k}) + \beta(w_{c,k} + \sigma^2), \quad \forall k \in D. \tag{11}$$

The iterations continue until the gap between $C(\mu^\tau)$ and $C(\mu^{\tau-1})$ is sufficiently small. Then the Lagrangian dual is solved. The solution y^τ in the final iteration gives a lower bound for the objective function value of problem (6), which corresponds to an upper bound for the original device pairing problem in (4). This solution matches each request device in D to one real or virtual cache device in S'. If a virtual cache device is matched, it is known that the SINR constraint is satisfied since the corresponding received signal power is set to be sufficiently large. However, if a request device is matched to a real cache device, the received SINR may not satisfy the minimum decoding threshold due to the Lagrangian relaxation. In the next section, we will introduce an augmentation algorithm that further derives a feasible pairing solution from the upper bound obtained by the above Lagrangian relaxation.

B. Augmentation Algorithm

Alg. 1 obtains a perfect matching that pairs each request device with a virtual or real cache device. As discussed above, the received SINR at these request devices may not satisfy the minimum decoding threshold due to the Lagrangian relaxation. Deriving a feasible solution 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. Thus, 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 $\hat{E}$.

Though Alg. 1 relaxes constraint (6d) of problem (6), the obtained solution satisfies the one-to-one matching constraints in (6b) and (6c). Thus, we can reduce (6) into a simpler version to determine a feasible solution to problem (6). For clarity, we replace the decision variable y_ℓ in (6) by another binary variable z_ℓ with respect to each candidate edge $\ell \in \hat{E}$. As $|\hat{E}| = |\hat{D}|$, we reorder the edges in $\hat{E}$ 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. Then, we can solve the following problem to obtain a feasible pairing solution:

$$\max_{z} \sum_{\ell\in\hat{E}} z_\ell \tag{12a}$$

$$\sum_{\ell\in\hat{E}} z_\ell(\beta w_{\ell,k} - p_{\ell,k}) \le -\beta(w_{c,k} + \sigma^2), \quad \forall z_k = 1, k \in \hat{D} \tag{12b}$$

$$z_\ell \in \{0,1\}, \forall \ell \in \hat{E}. \tag{12c}$$

Moreover, the condition in (12b) can be removed by considering a sufficiently large number Φ as follows:

$$\sum_{\ell\in\hat{E}} z_\ell(\beta w_{\ell,k} - p_{\ell,k}) \le (1 - z_k)\Phi - z_k\beta(w_{c,k} + \sigma^2), \forall k \in \hat{D}. \tag{13}$$

Rearranging this inequality, we have

$$\sum_{\ell\in\hat{E},\ell\ne k} z_\ell(\beta w_{\ell,k} - p_{\ell,k}) + z_k[(\beta w_{\ell,k} - p_{\ell,k}) + \beta(w_{c,k} + \sigma^2) + \Phi] \le \Phi, \forall k \in \hat{D}. \tag{14}$$

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

$$\xi_{\ell,k} = \begin{cases} \beta w_{\ell,k} - p_{\ell,k}, & \ell \ne k \\ (\beta w_{\ell,k} - p_{\ell,k}) + \beta(w_{c,k} + \sigma^2) + \Phi, & \ell = k. \end{cases} \tag{15}$$

Then, constraint (12b) can be rewritten as

$$\sum_{\ell\in\hat{E}} z_\ell \xi_{\ell,k} \le \Phi, \forall k \in \hat{D}. \tag{16}$$

Accordingly, problem (12) is reformulated as

$$\max_{z} \sum_{\ell\in\hat{E}} z_\ell \tag{17a}$$

$$\sum_{\ell\in\hat{E}} z_\ell \xi_{\ell,k} \le \Phi, \forall k \in \hat{D} \tag{17b}$$

$$z_\ell \in \{0,1\}, \forall \ell \in \hat{E}. \tag{17c}$$

Here, we can interpret the edges to be selected as items and each item has a multidimensional size $\xi_{\ell,k}$ toward each dimension k that corresponds to receiver device k. Then, constraint (17b) can be understood as a multidimensional knapsack that has a capacity limit Φ in each dimension. The problem aims to select a greatest number of items such that their total size satisfies the capacity limit for each dimension. Therefore, we can view problem (17) as an instance of the multidimensional knapsack problem (MDKP).

Based on the preceding analysis, we propose Alg. 2 to enhance the upper-bound perfect matching obtained by Alg. 1. In Line 1 to Line 16, Alg. 2 processes the upper bound to obtain a feasible solution that meets the SINR constraint. As seen, Alg. 2 begins with an all-zero solution $z_\ell = 0, \forall \ell \in \hat{E}$, and then iteratively includes more feasible edges from $\hat{E}$. As $\xi_{\ell,k}$ defined in (15) can be negative, for ranking purpose, we add a sufficiently large constant to each coefficient $\xi_{\ell,k}$ and obtain a positive value $\xi_{\ell,k}^+$. Also, we use a weight parameter, δ_k, which evaluates the occupancy of the existing selected edges with respect to each dimension k, i.e., $\delta_k \triangleq \sum_{\ell\in\hat{E}} z_\ell \xi_{\ell,k}^+$.

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Algorithm 2: Augmentation for device pairing.

Input: S, $\hat{D}$, $\hat{E}$, $\{\xi_{\ell,k} : \ell \in \hat{E}, k \in \hat{D}\}$, $\{w_{\ell,k} : \ell \in \hat{E}, k \in \hat{D}\}$, $\{w_{c,k} : k \in \hat{D}\}$, $\{\psi_{\ell,k} : \ell \in \hat{E}, k \in \hat{D}\}$, σ^2, β, ϵ, Φ
Output: $z = \{z_\ell : \ell \in \hat{E}\}$

1 **begin** Derive a feasible matching
2   Initialize solution $z_\ell \leftarrow 0, \forall \ell \in \hat{E}$
3   Convert coefficients $\xi_{\ell,k}$ to positive $\xi^+_{\ell,k}, \forall k \in \hat{D}$
4   Initialize weights $\delta_k \leftarrow 1, \forall k \in \hat{D}$
5   Initialize unpaired device sets: $\bar{S} \leftarrow S$, $\bar{D} \leftarrow D$
6   **repeat**
7   Compute weighted average size for each edge $\ell \in \hat{E}$: $\sum_{k\in\hat{D}} \delta_k \cdot \xi^+_{\ell,k}$
8   Sort unselected edges in ascending order of average size, denoted by $\hat{\mathbb{E}}$
9   **foreach** $\ell \in \hat{\mathbb{E}}$ **do**
            // Capacity constraint (17b) is satisfied
10   **if** $(\sum_{\ell'\in\hat{E}} z_{\ell'}\xi_{\ell',k} + \xi_{\ell,k}) \le \Phi, \forall k \in \hat{D}$ **then**
11   Set $z_\ell \leftarrow 1$
12   Update occupancy $\delta_k \leftarrow \sum_{\ell\in\hat{E}} z_\ell \xi^+_{\ell,k}, \forall k \in \hat{D}$
13   Update weighted average size for unselected edges according to new δ_k
14   Update edge and device sets: $\hat{E} \leftarrow \hat{E} \setminus \ell$, $\bar{S} \leftarrow \bar{S} \setminus \{j\}$, $\bar{D} \leftarrow \bar{D} \setminus \{k\}$, for $\ell = (j,k)$
15   Break
16   **until** *No feasible edge to add*
17 **begin** Enhance the feasible matching
18   Obtain sets of candidate cache devices from $\bar{S}$ for each request device $k \in \bar{D}$: $\{\bar{S}_k : \forall k \in \bar{D}\}$
19     $stop \leftarrow 0$
20   **repeat**
21   Sort unpaired request devices in $\bar{D}$ to $\bar{\mathbb{D}}$ according to ascending order of $|\bar{S}_k|, \forall k \in \bar{D}$
22   **foreach** $k \in \bar{\mathbb{D}}$ **do**
23   For each candidate cache device $j \in \bar{S}_k$, compute its total interference to existing device pairs: $\sum_{k'\in D\setminus\bar{\mathbb{D}}} w_{\ell,k'}$ for $\ell = (j,k)$
24   Sort candidate cache devices in $\bar{S}_k$ to $\bar{\mathbb{S}}_k$ in ascending order of above total interference
25             $cacheFound \leftarrow 0$
26   **foreach** $j \in \bar{\mathbb{S}}_k$ **do**
27   **if** *Capacity constraint (17b) is satisfied after adding pair* (j,k) **then**
28   Set $z_\ell \leftarrow 1$, for $\ell = (j,k)$
29   Update unpaired device sets: $\bar{S} \leftarrow \bar{S} \setminus \{j\}$, $\bar{D} \leftarrow \bar{D} \setminus \{k\}$
30   Remove cache device j from all candidate device sets $\bar{S}_k$ with it
31                     $cacheFound \leftarrow 1$ and Break
32   **if** $cacheFound = 1$ **then** Break
33   **else** $stop \leftarrow 1$
34   **until** $stop = 1$
35 Return z

As seen in Line 8, all unselected edges are ranked according to an average size weighted by δ_k. For an unselected edge ℓ, 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 MDKP [21]. The average size captures the overall demand of an unselected edge. The more capacity is occupied by existing selected edges in a dimension, the larger weight is counted for that dimension when the average size is computed. 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 (17b) 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 (17b) is satisfied. This procedure continues until every candidate edge is selected or no more feasible edge can be added.

After deriving a feasible matching solution, $\{\ell : z_\ell = 1 \text{ and } \ell \in \hat{E}\}$, Alg. 2 further augments it in Line 17 to Line 34 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 not only can add more feasible device pairs, but also restrict the interference impact in the meantime.

C. Swapping Algorithm

After Alg. 1 and Alg. 2, we are able to find a feasible matching φ that intends to pair as many devices as possible. For each edge $\ell = (j,k)$ with $z_\ell = 1$, we have $\varphi(k) = j$. As shown later in Section VI, these two steps can achieve near-optimal pairing performance. Nonetheless, the pairing result may not be most desired for each matched device. For instance, a request device may prefer another cache device to its existing partner for a higher transmission rate. As analyzed in Section IV-B, it is NP-hard to maximize the number of paired devices without considering the devices' individual utilities. In fact, it is extremely complex to simultaneously address both

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efficiency and stability in one optimization problem. Hence, we add a separate step to refine the pairing result to maintain system stability.

Specifically, we quantify the utility of a request device by its achievable data rate, i.e.,

$$u_k(\varphi) = \begin{cases} r_k(\varphi), & \text{if } \varphi(k) \neq \emptyset \\ 0, & \text{otherwise.} \end{cases} \tag{18}$$

Here, we explicitly include the matching φ in the utility function to highlight the dependence of a device's utility on the entire matching and not just toward its paired device. For comparison purpose, we further normalize the utility so that $0 < u_k(\varphi) < 1$ by using a sigmoid function for the difference between the achievable data rate r_k and the minimum rate requirement $r_{\min}$, given by

$$u_k(\varphi) = \begin{cases} \frac{1}{1+e^{-(r_k(\varphi)-r_{\min})}}, & \text{if } \varphi(k) \neq \emptyset \\ 0, & \text{otherwise.} \end{cases} \tag{19}$$

On the other hand, the cache devices are different from the request devices that usually pay monthly fees to the mobile network operator as cellular subscribers. The cache devices are often recruited on demand and paid by the BS to offload its traffic and reduce service cost. Here, we fix the transmit power of D2D transmitters such that they do not differentiate toward the request devices. Consider utilities of homogeneous cache devices that represent the system's interest. From the BS's perspective, an essential goal is to serve as many request devices as possible while maintaining certain level of QoS guarantee. Therefore, we evaluate the utility of any cache device j by the cardinality of the matching, i.e., the total number of served request devices:

$$u_j(\varphi) = \sum_{j' \in S} \mathbf{1}(\varphi(j') \neq \emptyset) \tag{20}$$

where $\mathbf{1}(\cdot)$ is an indicator function which outputs 1 if the condition in the function argument is true and outputs 0 otherwise. Similar to the utility definition for requesting devices, we can normalize the utility of caching devices by

$$u_j(\varphi) = \sum_{j' \in S} \mathbf{1}(\varphi(j') \neq \emptyset)/|S|. \tag{21}$$

It is worth noting that the utilities of a transmitter or receiver in (19) and (21) are defined not just toward its paired device but with respect to the matching φ. This is because the utilities are dependent on all D2D pairs in the matching due to the interference among the D2D links. Such a matching problem with *externalities* is significantly different from regular matching problems with independent preferences. Hence, many existing algorithms for stable matching, such as the deferred acceptance algorithm by Gale and Shapley [22], cannot be applied to this scenario.

Based on the utility definitions, we develop Alg. 3 to derive a stable matching from device pairs obtained by Alg. 1 and Alg. 2. Alg. 1 and Alg. 2 focus on the efficiency objective, i.e., pairing as many devices as possible, without the stability constraint. Thus, the solution obtained by Alg. 1 and Alg. 2 gives an upper bound for the case that the stability constraint is taken into count. Although Alg. 3 is a separate step to meet the stability constraint, it does not compromise the efficiency objective achieved by Alg. 1 and Alg. 2. This is because Alg. 2 only swaps some possible pairs to achieve system stability while improving device individual utilities, but it does not change the total number of paired devices.

Algorithm 3: Swapping for stable device pairing.

Input: S, D, E, φ, σ^2, β, ϵ, $\{p_{\ell,k} : \ell \in E, k \in D\}$, $\{w_{\ell,k} : \ell \in E, k \in D\}$, $\{w_{c,k} : k \in D\}$

Output: φ

1 Compute social welfare of current matching φ: $W(\varphi)$
2 $W_{\max} \leftarrow W(\varphi)$
3 $stop \leftarrow 0$
4 **repeat**
5   **foreach** $k_1 \in D, \varphi^{-1}(k_1) = j_1$ **do**
6   Identify swap candidates as set $S_{k_1} = \{j_2 : j_2 \in S, j_2 \neq j_1, \ell = (j_2, k_1) \in E, \varphi(j_2) = k_2 \neq \emptyset\}$
7   **foreach** $j_2 \in S_{k_1}$ **do**
8   Calculate utilities of $\{j_1, k_1, j_2, k_2\}$ with matching φ (noting $u_{j_1} = u_{j_2}$)
9   Calculate utilities of $\{j_1, k_1, j_2, k_2\}$ with swap matching φ_{j_1,j_2} (noting $u_{j_1} = u_{j_2}$)
10   **if** $u_{j_1}(\varphi_{j_1,j_2}) < u_{j_1}(\varphi)$ *or* $u_{k_1}(\varphi_{j_1,j_2}) < u_{k_1}(\varphi)$ *or* $u_{k_2}(\varphi_{j_1,j_2}) < u_{k_2}(\varphi)$ **then**
11   Skip current j_2
12   **else if** $u_{j_1}(\varphi_{j_1,j_2}) > u_{j_1}(\varphi)$ *or* $u_{k_1}(\varphi_{j_1,j_2}) > u_{k_1}(\varphi)$ *or* $u_{k_2}(\varphi_{j_1,j_2}) > u_{k_2}(\varphi)$ **then**
        // When swap condition is satisfied, exchange assigned partner devices
13         $\varphi(j_1) \leftarrow k_2$, $\varphi(j_2) \leftarrow k_1$
14   Update social welfare function $W(\varphi)$
15   **if** $W(\varphi) > W_{max}$ **then**
16     $W_{max} \leftarrow W(\varphi)$
17   **else**
18     $stop \leftarrow 1$
19 **until** $stop = 1$
20 Return φ

In Alg. 3, we allow two D2D pairs to swap their assigned partners, but need to ensure that such swaps converge to a stable matching. As seen in Line 10 to Line 14, two request devices that are paired with some feasible cache devices can only swap their assigned partners under certain condition. The swapping condition is related to a notion of stability for matching problems with externalities, referred to as *two-sided exchange stability* [23], whose definition is adapted to our context as follows:

Definition 1. *For a matching φ, a swap matching φ_{j_1,j_2} switches the partners of $j_1, j_2 \in S$, which are $k_1, k_2 \in D$, respectively, i.e., $\varphi(j_1) = k_1$ and $\varphi(j_2) = k_2$, while keeping all other pairs. Then, the matching φ is two-sided exchange stable if and only if there do not exist two device pairs (j_1, k_1) and (j_2, k_2), such that*

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i) $\forall i \in \{j_1, k_1, j_2, k_2\}, u_i(\varphi_{j_1,j_2}) \geq u_i(\varphi)$; *and*
ii) $\exists i \in \{j_1, k_1, j_2, k_2\}, u_i(\varphi_{j_1,j_2}) > u_i(\varphi)$.

In other words, a swap is approved by both sides only if the utility of each involved device is not decreased while the utility of at least one device is strictly increased. When no such swap is possible, the matching attains two-sided exchange stability.

To prove that Alg. 3 converges to a two-sided exchange stable matching, we define a social welfare function as

$$W(\varphi) = \sum_{k \in D} u_k(\varphi) + \sum_{j \in S} u_j(\varphi) \tag{22}$$

which is the social welfare function is the total utilities of all paired devices. Next, we prove the following theorem regarding the convergence and stability of Alg. 3.

Theorem 2. *Alg. 3 converges to a two-sided exchange stable matching that achieves a local maximum of the social welfare function.*

Proof. As seen in Line 4 to Line 19 of Alg. 3, the loop terminates when the social welfare function $W(\varphi)$ cannot be further increased via swaps, which implies that a local maximum of $W(\varphi)$ is reached. By contradiction, assume that the matching φ for the local maximum of $W(\varphi)$ is not two-sided exchange stable. It means that there exist two D2D pairs (j_1, k_1) and (j_2, k_2) in φ that a swap of the partners of the two pairs satisfies conditions i) and ii) in Definition 1. Comparing the social welfare function of φ and φ_{j_1,j_2} resulting from the swap, we have

$$\begin{aligned} W(\varphi_{j_1,j_2}) - W(\varphi) = &\sum_{k \in D} u_k(\varphi_{j_1,j_2}) + \sum_{j \in S} u_j(\varphi_{j_1,j_2}) \\ &- \sum_{k \in D} u_k(\varphi) - \sum_{j \in S} u_j(\varphi). \end{aligned} \tag{23}$$

Notice that the swap of partners of pairs (j_1, k_1) and (j_2, k_2) will not change the interference caused by transmitters j_1 and j_2 to other D2D receivers except for k_1 and k_2. This is because j_1 and j_2 are still actively transmitting but just toward different receivers. Hence, the SINR perceived at irrelevant D2D receivers are not affected. Therefore, we cancel the unchanged terms in (23) and rewrite it as

$$\begin{aligned} W(\varphi_{j_1,j_2}) - W(\varphi) = &[u_{j_1}(\varphi_{j_1,j_2}) - u_{j_1}(\varphi)] \\ &+ [u_{j_2}(\varphi_{j_1,j_2}) - u_{j_2}(\varphi)] \\ &+ [u_{k_1}(\varphi_{j_1,j_2}) - u_{k_1}(\varphi)] \\ &+ [u_{k_2}(\varphi_{j_1,j_2}) - u_{k_2}(\varphi)]. \end{aligned} \tag{24}$$

According to i) and ii) in Definition 1, all four subtraction terms in (24) are non-negative and at least one subtraction result is positive. Then, we have $W(\varphi_{j_1,j_2}) > W(\varphi)$, which contradicts the above assumption that matching φ achieves the local maximum of the social welfare function. Therefore, Alg. 3 converges to a two-sided exchange stable matching. □

VI. 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 power levels of D2D transmitters and cellular user are set to P_d = 100mw and P_c = 100mw, respectively. 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 $\gamma_c = 0.9$ [24]. The default SINR decoding threshold β is set to 2. The path-loss exponent and noise variance are set to $\alpha = 4$ and $\sigma^2 = 5 \times 10^{-10}$mW, respectively.

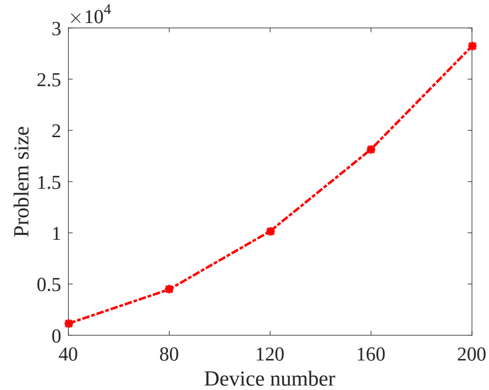

Fig. 4: Properties of simulation datasets.

In addition to our proposed algorithms, we consider three reference schemes that derive the device pairing for D2D-assisted data dissemination.

- The optimal solution – The device pairing problem in (6) can be solved by the GNU Linear Programming Kit (GLPK) package [25] when the problem size is small.
- A heuristic channel-aware scheme – Based on the approach proposed in [13], the request devices are considered one by one according to a certain order. Each request device under consideration is paired to the feasible cache device of 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 [16] 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, in the swap phase, each matched request device keeps searching for a new request device to form a swap-blocking pair for swapping until the matching becomes two-sided exchange stable. For comparison fairness, we define the utilities of request and cache devices in the same manner as in our scheme.

A. Properties of Datasets

In this subsection, we want to illustrate the properties of simulation datasets. Fig. 4 shows the number of edges of the bipartite graph in Fig. 2 when the number of request devices and that of cache devices are set to be the same and increase from 40 to 200. The corresponding problem size of the device pairing problem is exponential with respect to the number of

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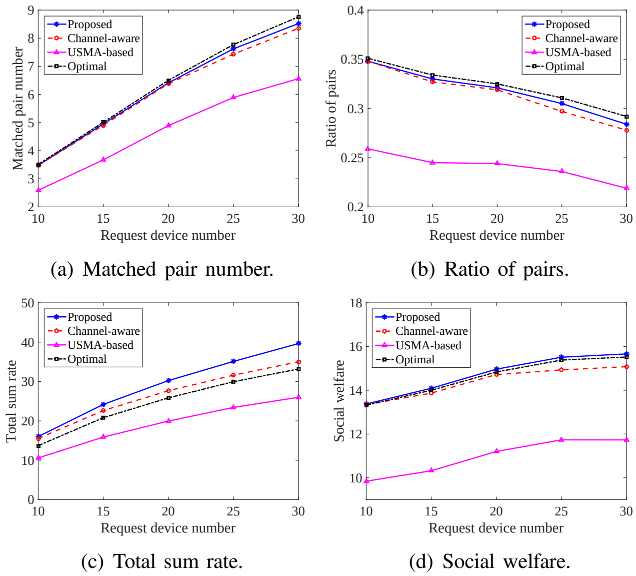
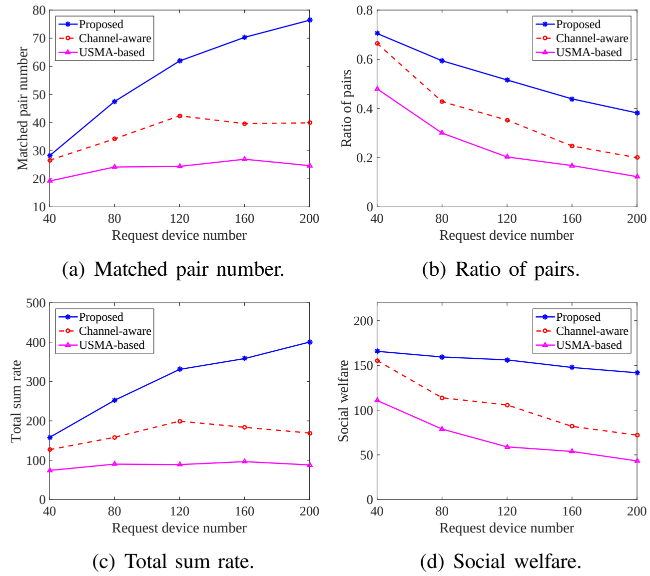


(a) Matched pair number. (b) Ratio of pairs. (c) Total sum rate. (d) Social welfare.

Fig. 5: Performance with a different number of request devices in small-scale networks.



(a) Matched pair number. (b) Ratio of pairs. (c) Total sum rate. (d) Social welfare.

Fig. 6: Performance with a different number of request devices in large-scale networks.

edges shown in Fig. 4. As seen, when the network scale is relatively small, the number of potential available D2D links is already so large, which makes it difficult to obtain the optimal pairing. Moreover, it is observed that as the numbers of request devices and cache devices increase, the corresponding problem size and computational difficulty grow rapidly.

B. *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. First, we run simulations with relatively small-scale networks. Specifically, 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.

Fig. 5(a) and Fig. 5(b) show the number of matched pairs and the ratio of the pair number to the number of request devices, respectively. With the increase of the number of request devices, the number of matched pairs increases, but the ratio of pairs decreases correspondingly. Also, the performance of our approach is 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. Fig. 5(c) and Fig. 5(d) show the total sum rate per Hz and social welfare, respectively. As seen in Fig. 5(c), our approach achieves the highest sum rate. Although the channel-aware scheme tends to match pairs with high achievable data rates, the heuristic nature limits the overall performance. The USMA-based scheme also uses a swapping procedure, but its initial matching is not so optimized as the matching obtained by Alg. 1 and Alg. 2.

Moreover, we run simulations with large-scale networks. Here, the number of cache devices is set to 200, while the number of request devices increases from 40 to 200. As analyzed in Section IV-B, the device pairing problem is NP-complete. When the network scale becomes large, it is extremely difficult to obtain the optimal solution. Therefore, in the following, we only compare our approach with the channel-aware scheme and the USMA-based scheme. Fig. 6 show the corresponding performance of the three device pairing schemes. It can be seen that the gap between our approach and the reference schemes becomes more significant when the network scale is larger. Specifically, Fig. 6(a) shows that our approach can pair more devices with the increase of request devices, while the two reference schemes do not improve so evidently. Similarly, Fig. 6(c) shows that our approach achieves a much higher sum rate, which grows rapidly with the number of request devices. In addition, it is worth noticing that the social welfare of the above schemes increases with more request devices in the small-scale network while it decreases in the large-scale network. This is because, as the number of request devices increases to a much higher order, the ratio of matched pairs and correspondingly the system utility decrease.

C. *Effect of Number of Cache Devices*

In this subsection, we evaluate the effect of cache devices on the pairing performance. Similar to Section VI-B, we first run simulations with small-scale networks and then increase the network size to a large scale. For the small-scale networks, the number of request devices is fixed at 30, while the number of cache devices increases from 30 to 50. Fig. 7 shows the result of four pairing schemes in the small-scale networks. As seen in Fig. 7(a), when there are more cache devices available in the network, more request devices are successfully paired. Correspondingly, the social welfare in Fig. 7(b) increases since there exist more D2D communication pairs. In addition, it is observed that the proposed approach performs closely to the optimal solution and achieves a minor performance gain over the reference schemes.

Further, we increase the number of request devices to 100 and vary the number of cache devices from 100 to 200. Due to computational intractability, the optimal solution is

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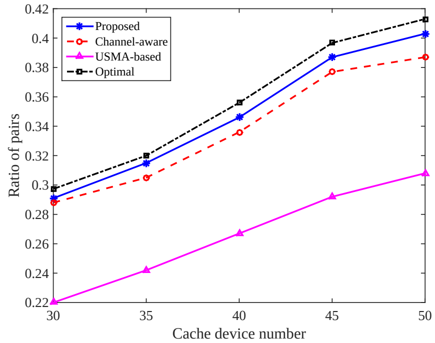
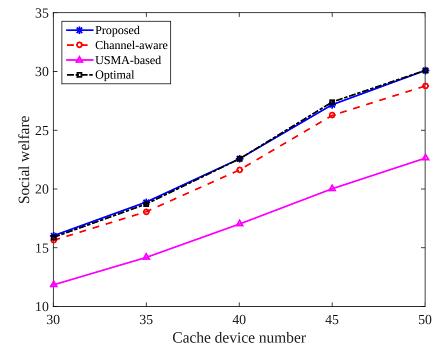
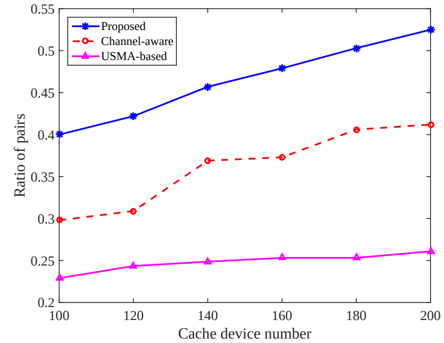


(a) Ratio of pairs.

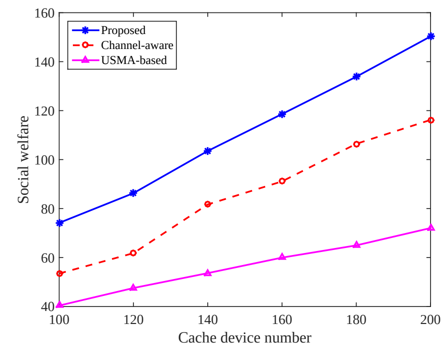


(b) Social welfare.

Fig. 7: Performance with a different number of cache devices in small-scale networks.



(a) Ratio of pairs.



(b) Social welfare.

Fig. 8: Performance with a different number of cache devices in large-scale networks.

omitted. Fig. 8 shows the performance in terms of the ratio of matched pairs and social welfare. As seen, the performance gap between the proposed approach and the reference schemes grows significantly with a larger network scale.

D. Effect of Caching Capacity of Cache Devices

It is obvious that not only the number of cache devices but also their caching capacities determine the available resources to serve requests. Hence, in this subsection, we fix both the number of request devices and that of cache devices to 100, but vary the caching capacity of each cache device from 2 to 10 messages. Fig. 9 shows the performance of three pairing schemes in terms of the ratio of pairs and social welfare. It is observed that the performance varies similarly with caching capacities as with the number of cache devices in Fig. 8. This can be explained easily, since more cache devices or larger caching capacities both contribute more resources to the network and thus lead to similar variation trends.

E. Effect of SINR Decoding Threshold

Last, we conduct experiments to examine the effect of SINR decoding threshold β. Similar to Section VI-D, the number of request devices and that of cache devices are both set to 100. When the SINR decoding threshold is changed from 2 to 6, Fig. 10 shows the corresponding performance. Consistently, it is observed that our proposed approach performs the best with different SINR decoding thresholds. In addition, the ratio of pairs and social welfare of all three schemes decrease with SINR decoding threshold. This is expected because 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, which leads to a lower social welfare.

VII. 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 can be utilized efficiently to serve message requests. Our analysis shows that the pairing problem is NP-complete in its decision form and NP-hard in its optimization form. To address the computational hardness, we propose a three-step approach that derives a near-optimal and stable device pairing. In particular, by transforming the device pairing problem into a one-to-one matching problem with externality, we prove that the proposed approach is guaranteed to converge to a two-sided exchange stable matching. Extensive simulation results further demonstrate the effectiveness of our approach. It is shown that the proposed approach performs closely to the optimal solution in a small-scale network. Moreover, in large-scale networks, the proposed approach achieves significant performance gain over two existing schemes.

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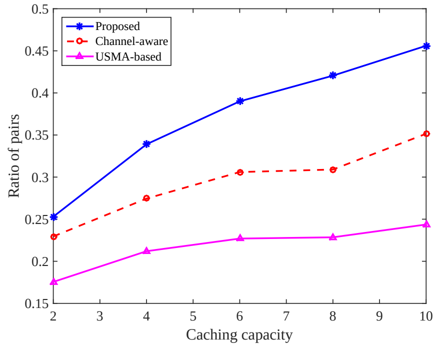
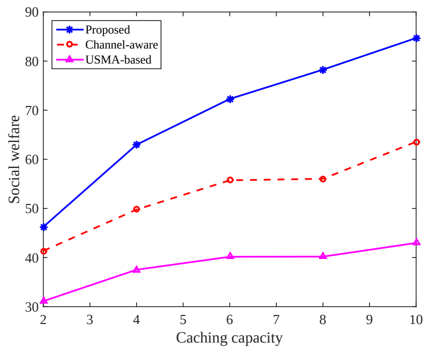
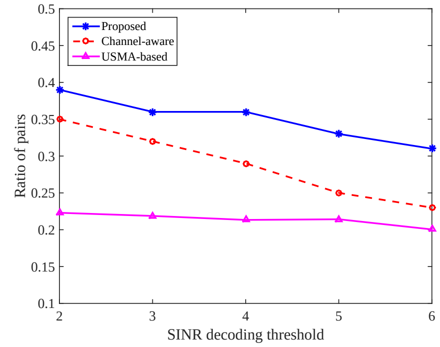


(a) Ratio of pairs.

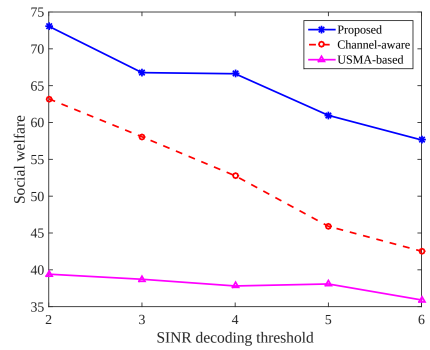


(b) Social welfare.

Fig. 9: Performance with a different caching capacity for each cache device.



(a) Ratio of pairs.



(b) Social welfare.

Fig. 10: Performance with a different SINR decoding threshold at request devices.

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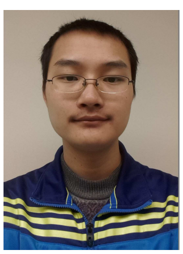

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