Distributed Resource Allocation Approach For Device-to-Device Multicast Communications

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***Abstract*—In this paper, we address the problem of joint resource and power allocation in underlay device-to-device multicast communication for short (D2MD) to maximize system global energy efficiency (GEE). For this, we propose a two-stage semi-distributed solution. First, we model the resource sharing sub-problem as a transferable overlapping coalition formation game. Here, a D2MD group can participate in s coalitions and it can decide to join or leave a coalition based on specific split and merge rules. Similarly, a resource block can be shared among r D2MD groups where s, r are reuse and split factors. After that, the transmission power is centrally controlled by the The base station (BS) via a fractional programming framework. Finally, GEE is analysed via extensive numerical simulations with a spatial Poisson process for the users' locations and applying two different clustering algorithms: K-nearest neighbour, and distance-limited.**

***Index Terms*—Game Theory, overlapping coalitions, Resource Allocation, D2D multi-casting communication, 5G wireless networks.**

I. Introduction

Underlay device-to-device communication (D2D) [1] is a promising low-cost technique to save resources in 5G cellular networks. It allows users in close proximity to communicate directly without the intervention of a central entity as a base station (BS) or an access point (AP) using cellular users resource blocks (RB). This short-range communication provides high data rate transmission, thus reduces transmission time, increases network capacity and energy efficiency. Sharing RBs helps to cope with the scarcely available resources problem, yet it may result in harmful mutual interference between cellular (CUE) and D2D users which degrades communication quality. Moreover, the problem becomes more complicated as the number of D2D users per RB increases due to interference accumulation on CUE from all D2D users and on D2D pairs from CUE and other pairs sharing the same resources. Therefore, it is critical to control inter-pair and accumulated interference on the CUEs. The existence of a single receiver in the communication is simply a unicast topology, i.e., D2D pair, whereas in multicast we have at least two receivers, i.e., a cluster or a group referred to as D2MD. Compared to unicast mode, multicast reduces overhead signals and saves more communications resources. In addition, this topology has a wide range of applications as public safety, vehicle communication, common content distribution, proximity-based group gaming and advertisement,. . . etc. However, it is more challenging in terms of interference mitigation, because cluster data rate is determined by the worst channel to guarantee that all the receivers are able to decode the transmitted data. In addition, it brings new questions to answer concerning the selection of the head cluster and the clustering techniques. To manage the interference, researchers have investigated both joint and separate resource allocation and power control techniques, as illustrated in [2]. In [3], the problem of joint power control and resource allocation in D2MD scenario has been studied with the goal of maximizing the system throughput. As this is a MINLP (mixed integer nonlinear problem), it was divided into two sub-problems where the first solves the optimal power allocation and the feasible channel subset. Then, a bipartite graph is constructed and solved using the Hungarian algorithm. Later, they extended their work in [4] to consider a scenario where multiple D2MD groups can use many CUE channels, with a comparison between a greedy and a heuristic algorithm. With a similar concept, the authors in [5] modelled the problem using a multi-objective optimization framework with weighted factors to minimize energy consumption while maximizing the number of served links in D2MD groups. In [6], the problem was formulated too as MINLP where D2MD groups can use all the available cellular channels to maximize the minimum throughput, and was solved in two stages where the second stage uses a genetic algorithm. To this end, we notice that all the proposed solutions are centralized and mainly target system throughput maximization. In such case, a central entity is in charge for the pairing of D2MD and CUEs, and imposes constraints on transmission power to limit interference and to guarantee the communication quality. Therefore, centralized approaches help to achieve the best possible solution. However, the assumption that the central controller has complete information about the users transmission parameters and channels qualities is not reasonable in reality. Moreover, as the number of users grows, problem complexity and the amount of overhead signals explode, so controller might suffer from congestion. In contrast to the available research works, we propose a two-stage semi-distributed resource management and power control framework for D2MD communication in cellular networks to maximize the system global energy efficiency (GEE). The addressed solution takes advantage of the centralized approach in terms of high energy efficiency, and has low control overhead from the distributed one. First, we use an

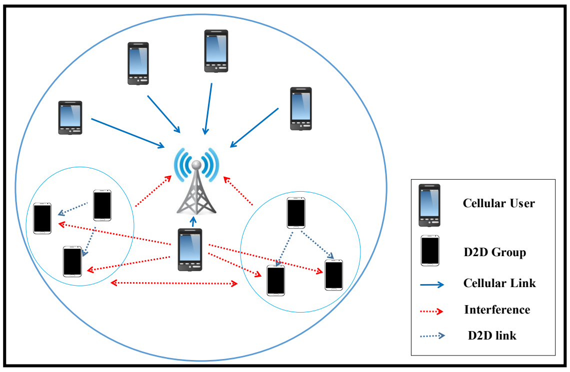

Fig. 1: System Model.

overlapped coalition formation game to model the resource allocation sub-problem. Here, D2MD groups are able to self-organize themselves into a stable overlapped partition, so-called coalitions. To do this, we develop a distributed coalition formation algorithm based on the merge-and-split rules which considers maximum transmission power and minimum rate constraints. The proposed game-theoretic framework considers a reuse factor r i.e. the maximum number of D2MD clusters per RB and a split factor s i.e. the maximum number of RB a D2MD cluster is allowed to use. Secondly, the power allocation is determined by the BS using a low-complexity fractional programming optimization framework. Finally, to characterize the system behaviour in terms of global energy efficiency (GEE) and aggregated rate, we solve numerically the combined framework with a stochastic geometry and various clustering techniques. The rest of the paper is organized as follow. We first present the system model in Section II. Next, we introduce our optimization problem in Section III. Then, in Section IV we detail coalition formation game model and split-and-merge algorithm. After that, we addressthe power control algorithm in Section V. Later, we discuss results and numerical experiments in Section VI. Finally, we conclude in Section VII.

II. System Model

In this paper, we analyse a single cell environment with one base station (BS) located in the origin and with uniformly distributed users, see Figure 1. On the uplink, M cellular users (CUEs) transmit on M orthogonal communication channels.[1] Here, the term m shall be used to refers to CUE users, resource blocks (RB) and channels interchangeably. Reusing downlink resources requires sophisticated coordination between users equipments and the BS, and has been shown to be less effective than uplink resource sharing. Therefore, we assume the coexistence of K multicast D2MD clusters $k = 1, \dots, K$, that reuse the same communication channels allocated to CUEs for their direct communication. Each group has one designated transmitter called head cluster (HC) and $|\mathcal{G}_k|$ receivers. The selection of HC and cluster formation will be detailed in section VI. The special case where $|\mathcal{G}_k| = 1$ is simply a unicast communication [4]. During the uplink phase, the BS suffers from interference caused by the co-channel D2MD transmitters. Similarly, the $|\mathcal{G}_k|$ receivers of group k receive interference coming from the cellular users and from other transmitters in D2MD groups sharing the same resource block. The SINR of a D2D receiver Rx in group k and channel m is given by

$$\mathsf{SINRd}_{k,m,Rx}(\{\mathbf{p}_k\}_m, p_m) = \frac{h_{k,m,Rx} p_{k,m}}{\sigma^2 + p_m \beta_{k,m,Rx} + \sum_{j \neq k} I_{j,m} p_{j,m} h_{j,m,Rx}} \tag{1}$$

where $h_{k,m,Rx}$ are the channel coefficients from the transmitter in group k to receiver Rx on channel m, and $\beta_{k,m,Rx}$ is similarly the link gain factor from CUE transmitter m to receiver Rx in group k. Symbol $p_{k,m}$ denotes the transmission power of the D2MD transmitter in group k on channel m, and p_m is the transmission power of CUE user m. For a CUE user m, the SINR is similarly given by

$$\mathsf{SINRc}_m(\mathbf{p}_k, p_m) = \frac{h_m p_m}{\sigma^2 + \sum_k I_{k,m} p_{k,m} h_{k,m}}, \quad m = 1, \dots, M \tag{2}$$

where h_m is the link gain from user m to the base station, p_m is the transmitted power, $h_{k,m}$ is the link gain from the transmitter in D2D group k to the cellular base station on channel m and $I_{k,m}$ are the indicator variables $I_{k,m} = \mathbb{1}_{\text{D2D group } k \text{ uses channel } m}$. The transmission rate (normalized in bits/s/Hz) of CUE m is then

$$r_m = \log_2(1 + \mathsf{SINRd}_m), \quad m = 1, \dots, M. \tag{3}$$

For D2MD group k, the unique transmission rate is determined by the weakest receiver, i.e., by the receiver with the poorest channel quality. In addition, we account explicitly for the aggregated received rate in group k, which depends on the number of receivers per group $|\mathcal{G}_k|$. Thus,

$$R_k = \sum_{m=1}^{M} I_{k,m} |\mathcal{G}_k| \min_{Rx \in \mathcal{G}_k} \log_2(1 + \mathsf{SINRd}_{k,m,Rx}), \tag{4}$$

for $k = 1, \dots, K$.

III. Joint power and channel allocations

The energy efficiency (EE) of a given user, measured in bits/Joule, is the ratio of the achievable transmission rate and the total consumed power. However, this is a user-centric definition for EE. To present the global network energy efficiency (GEE) η, we consider the ratio of the aggregated rate and the total consumed powers. More formally, if $\mathbf{r}$ and $\mathbf{R}$ are the vectors of rates for CUE and D2MD groups, respectively and s_c is the total circuit power network devices, then

$$\eta \triangleq \frac{\|\mathbf{r}\|_1 + \|\mathbf{R}\|_1}{s_c + \sum_k \|\mathbf{p}_k\|_1 + \|\mathbf{p}\|_1} \tag{5}$$

The GEE targets the total performance of the cellular network, thus

$$\max_{\mathbf{p}, \mathbf{I}_k \in \mathcal{P}} \eta$$

[1]The analysis with NOMA (non-orthogonal multiple access) is out of the scope of this paper.

$$= \frac{\sum_m \log_2(1+\mathsf{SINRc}_m) + \sum_k \sum_m I_{k,m}|\mathcal{G}_k| \log_2(1+\min_{Rx} \mathsf{SINRd}_{k,m,Rx})}{s_c + \sum_k \|\mathbf{p}_k\|_1 + \|\mathbf{p}\|_1} \tag{6}$$

where $\mathcal{P}$ is the feasible set of power vectors; namely, the set defined by the constraints

$$\sum_m \mathbf{p}_{k,m} \le \overline{p}_k, \quad k=1,\dots,K \tag{6a}$$
$$p_m \le P_m, \quad m=1,\dots M \tag{6b}$$
$$\underline{R}_k \le R_k, \quad k=1,\dots,K \tag{6c}$$
$$\underline{r}_m \le r_m, \quad m=1,\dots,M \tag{6d}$$
$$\sum_m \underline{R}_{k,m} \le R, \quad m=1,\dots,M \tag{6e}$$
$$\mathbf{I}_k \in \{0,1\}^M \quad \|\mathbf{I}_k\|_1 \le s \tag{6f}$$
$$\|\mathbf{I}_{\cdot,m}\| \le r \tag{6g}$$
$$(\mathbf{p},\mathbf{p}_1,\dots,\mathbf{p}_K) \in \mathbb{R}_+^{(K+1)\times M}. \tag{6h}$$

Here, constraints (6a)-(6b) bound the maximum power per user for CUE and the distributed power over s RB for D2MD; constraints (6c)-(6d) are the minimum rate conditions, where the rates have been defined in (3) and (4); constraints (6e) is introduced to control D2MD rate distribution over s RB; constraint (6f) enforces the maximum split factor s for every D2MD group; constraint (6g) is the maximum reuse factor r per sub-carrier; and finally (6h) is simply the non-negativity of all the power vectors. Clearly, (6f)-(6g) are the integer constraints, (6c)-(6d) are the coupling constraints on the transmission powers, and the set $\{\mathbf{p}_k\}$ are the coupling variables of the problem. Finally, note that the QoS constraints (6c)-(6d) are *user-specific*. The problem at hand is essentially a combination of decision making, i.e., the association of groups to channels, and an optimization part, namely the choice of the optimal transmission powers. The coupling between discrete and continuous variables turns the problem to a MINLP that is NP-hard so hard to get an optimal and satisfactory solution, as the complexity increases exponentially with the problem size. Therefore, it can be decoupled into two sub-problems: (a) the resource sharing problem for cellular users and D2MD groups based on the constraint of splitting and re-user factors; and (b) the power allocation problem for D2MD head cluster and cellular users based on constraints of minimum rate and maximum power on channel m or vice versa.

Resource Sharing Feasibility

The case where a D2MD user k_i aims to use the resource of a cellular user m_i admits a simple, closed-form sufficient and necessary conditions for pairing feasibility can be given, a result easily adapted from [7]. The proof is given in the Appendix.

Theorem 1. *Define $\underline{\gamma}_k = 2^{\underline{r}_k} - 1$ for $k = 0,\dots,K$, and the matrix*

$$W = [W]_{k,j} \triangleq \begin{cases} 0, & j = k \\ \frac{h_{k,j}\underline{\gamma}_k}{h_k}, & j \neq k. \end{cases} \tag{7}$$

A solution to the problem in hand, exists if and only if the spectral radius of W is less than one and

$$(I-W)^{-1}\underline{\mathbf{s}} \le \overline{\mathbf{p}} \tag{8}$$

where $\overline{\mathbf{p}} = [\overline{p}_0,\dots,\overline{p}_K]^T$ and $\underline{\mathbf{s}}$ has elements $s_j = \sigma^2\underline{\gamma}_j/h_j$.

Thus, Theorem 1 gives us an easy-to-check condition for feasibility of a power vector $\mathbf{p}$, one whose verification is straightforward while minimum rate can be evaluated using equations 3 and 4 for CUE and D2MD users, respectively.

IV. Overlapping Coalition Game

In this Section, we briefly review some important concepts from game theory. The framework of cooperative games provides the proper tools to model and develop autonomous, self-organizing techniques to form cooperative groups between players (the so-called coalitions) according to mutual benefits and costs [8]. In particular, a coalition can be seen as an agreement between various players to act as a single entity to achieve higher gain. We formally define the game as follows.

Definition 1. *A coalition game $\mathbf{G}$ is defined by the triplet $(\mathcal{N}, \mathsf{v}, \mathbf{S})$, where $\mathcal{N}$, is a set of players who seek to form cooperative groups or coalitions $\mathbf{S}$, such as $\mathbf{S} = \{S_1, S_2, \dots, \dots, S_M\}$ and any coalition $S_i \subseteq \mathcal{N}$ for $i = 1\dots M$ and v can be considered as a mapping function that determines players $\mathcal{N}$ pay-offs within the game $\mathbf{G}$.*

Here, $\mathcal{N} = M \cup K$, where M and K are the sets of CUE users and D2MD clusters, respectively, and v is a characteristic function that quantifies the worth of a coalition, i.e. a mapping that determines the player pays-off within the game $\mathbf{G}$. In our context, each coalition is composed of a single cellular user m and up to r D2MD groups, where r is a reuse factor to identify the maximum number of groups allowed to share a channel m. This restriction on the number of D2MD clusters is set to balance the increase in data rate and the cost of consumed energy as shown in [9]. The cellular and D2MD groups cooperate to minimize the total mutual interference among them and thus, increases system global energy efficiency. Therefore, S_i's coalition value $\mathsf{v}(S_i)$ represents the total mutual interference among users in the same group, and the characteristic function v depends only on the coalition members, but ignores how the remained players are partitioned. As a result, we have a coalition game with transferable utility (TU). In addition, the TU property allows to divide the coalition's total utility in any manner between its members. Thus, the game adapts a group-rational perspective [10]. To calculate v for a coalition S_i, we first compute the received interference on each side. For $k = 1,\dots,K$, D2MD groups the interference is determined by the weakest receiver as follow:

$$\alpha_{k,m} = \max_{Rx\in\mathcal{G}_k} p_m\beta_{k,m,Rx} + \sum_{j\neq k} I_{j,m}p_{j,m}h_{j,m,Rx} \tag{9}$$

and on CUE for $m = 1, \ldots, M.$,

$$\Gamma_m = \sum_k I_{k,m} p_{k,m} h_{k,m} \tag{10}$$

Thus, the coalition value, for $\forall k, m \in S_i$, is

$$\mathsf{v}(S_i) = \Gamma_m + \sum_k \alpha_{k,m} \tag{11}$$

It is worth to mention, that the coalition formation game is not super-additive. This implies that users will never form a single, grand coalition. In such case, the high interference value will force a player to be selfish and act as in a non-cooperative model.

Definition 2. *A coalition game with a TU is said to be non-super-additive if two coalitions $S_i, S_j \in \mathbf{S}$, $v(S_i \cup S_j) \leq \mathsf{v}(S_i) + \mathsf{v}(S_j)$ with $S_i \cup S_j \in S'$, where S' is another coalition structure different from* $\mathbf{S}$.

Generally, coalition formation games allow forming disjoint partitions where a player cannot participate in more than one coalition. Slightly different in this work, a device can appear in s coalitions simultaneously. In such case, a flexible coalition structure allows players to distribute their resources (power and rate) among the various coalitions in which they are part of. This can be highlighted by introducing a split factor s that limits the number of coalitions a player can participate at. In our particular context, a D2MD head cluster has a limited transmission power budget, denoted by P_{max}, which it can be split over maximum s channels, and a minimum total rate to attain. As a result, the model turns out to be an overlapping coalition formation game, or OCFG for short. The overlapping model leads to a better-organized coalition and possibly higher pay-offs, and holds all the previous definitions [11].

A. Merge-and-Split Algorithm

Initially, we consider that each device, i.e. CUE or D2MD, is a single coalition, and we seek to merge and split the isolated coalitions until M coalitions are formed, each including a single CUE user and up to r D2MD clusters. The members of a coalition are the set of devices that cause the minimum mutual interference to each other. Moreover, a D2MD cluster is able to participate in s coalitions simultaneously. In this paper, we aim at minimizing harmful users' mutual interference in order to maximize global energy efficiency while guaranteeing the QoS of each CUE and D2MD groups. To do this, we need a preference relation to compare between coalitions defined in 3, and also rules to identify under which conditions a D2MD cluster may break from or join a particular coalition. We will refer to these as merge and split rules, defined in 12.

Definition 3. *A preference or comparison relation $\triangleright$ is an order defined for comparing two collections. Consider coalition structure $\mathbf{S} = \{S_1, \ldots, S_m\}$, if a D2MD cluster k splits from S_1 and merges in to another existing coalition S_m, a new structure is formed $\mathbf{S}' = \{S'_1, \ldots, S'_m\}$ with $S'_1 = S_1 \setminus \{k\}$ and $S'_m = S_m \cup \{k\}$. Then, the switching order $\triangleright_s$ means that S' prefers to S for k.*

Every user is considered as a single coalition. Here, a D2MD group is willing to participate in s coalitions. The case when $s = 1$ is a typical coalition formation game. The join or merge decision is affected by the accumulated interference on CUE from clusters or on D2MD from CUE and other groups. Thus, merge and split rules must identify the set of CUEs, clusters that cause the lowest mutual interference to each other and to the cellular user and vice versa. This is defined as follows.

$$S \triangleright_s S' \Leftrightarrow \begin{cases} \mathsf{v}(k, S') < \mathsf{v}(k, S) \\ \mathsf{v}(S_1\prime, S') < \mathsf{v}(S_1, S) \\ \mathsf{v}(S') < \mathsf{v}(S) \end{cases} \tag{12}$$

From 12, the preference order $\triangleright_s$ implies that three conditions should be satisfied for k: (i) the individual received interference of k i.e. on the weakest receiver decreases; (ii) the total received mutual interference of coalition S'_1 which k newly merged into does not increase; and (iii) the interference in the new coalition structure S' decreases. Algorithm 1 illustrates how the split and merge works. Here, two types of interference are considered, the accumulated on CUE users from all D2MD groups in the coalition, and inter-clusters interference. Therefore, every time a single D2MD group merges or splits from a coalition that includes CUE users thus, the reuse factor is set to 1. In line 4, D2MD groups choose their initial transmission power based on theorem 1. Next, the minimum rate constraints are evaluated using 4, such that the CUE transmission power is initiated by the central unit, i.e. the BS (line 5). Later, each group k sorts the list of feasible coalitions, i.e., that currently includes CUE users only, based on the received interference with 9 (line 6). The first round starts when a group k sends a cooperation request to a coalition m. If the pairing/merge is feasible for the CUE via 1, and it had not been merged with any D2MD group $k\prime$, then a merge action takes a place and the CUE updates its transmission power (lines 9-11). The process continues until the split factor s is satisfied, or k is rejected from all the preferred coalitions. Else, if the coalition m is composed of a CUE and a D2MD group k', at the moment of receiving k's request then the rules discussed in 12 are evaluated. In this case, if the merge with k results in less interference, then k' leaves coalition m, so k and m merge. Hence, the reuse factor is set to 1, and in turn some D2MD groups may split from all the preferences or do not satisfy their split factor. Therefore, these groups recalculate the received interference from the formed coalitions, i.e., that includes CUE and D2MD group (line 23) where all the CUEs increase their reuse factor by 1 when they no longer receive any requests.

B. Convergence and Stability

Starting from an initial coalition structure, the convergence of the OCFG algorithm is guaranteed. Hence, for a given number of D2MD clusters and CUEs, the different coalition structures that can be formed are a finite number where each split-merge action results in a new coalition structure with lower interference values than the previous one. In addition, the proposed algorithm prevents D2MD groups from sending

Algorithm 1 Coalition Formation Algorithm

Set reuse factor = 1
repeat
  while coalition capacity $< r$ **do**
    Calculate D2MD transmission power (theorem 1)
    Calculate D2MD rate on all M (eq.4)
    Sort feasible coalitions in ascending order (eq.9)
    repeat
      A group k send a request to m
      if m capacity $< r$ and m, k is feasible **then**
        k merge with m
        update members transmission power
      else if m is merged with k', k is more preferred (eq.12) and m, k is feasible **then**
        k' split from the coalition m
        m merge with k
      else
        Keep k' and reject k
      end if
      if k is rejected by $\forall m \in M$ **then**
        k update interference based on eq.9
      end if
    until all k preference are tested || s is satisfied
    CUE Increase reuse factor by 1
    un-merged D2MD cluster update sorted list of coalitions from (eq.9)
  end while
until convergence to a stable $\mathbf{S}$

cooperation requests to coalitions that reject them, thus the game is guaranteed to reach a final stable coalition structure with overlapped coalitions.

Definition 4. *A structure is a $\mathbb{D}_{hp}$-stable if it can not be changed by the merge-and-split process.*

Assume that we have a final stable structure $\mathbf{S}_{fin}$, that can not be changed by the proposed algorithm as defined above. So, for any D2MD $k \in S_i$, where $S_i \in \mathbf{S}_{fin}$ and any coalition $S' \in \mathbf{S}_{fin}$ if $\mathsf{v}(S \setminus \{k\}) + \mathsf{v}(S' \cup \{k\}) > \mathsf{v}(S) + \mathsf{v}(S')$, then this contradicts the fact that $\mathbf{S}_{fin}$ is final. Therefore, $\mathbf{S}_{fin}$ is $\mathbb{D}_{hp}$ stable as defined above. Moreover, the resultant structure corresponds to the socially optimal solution because the proposed game $\mathbf{G}$ has a transferable utility [10].

V. Power Control

Once split and merge algorithm is completed and a stable finite coalition structure is reached, the power allocation sub-problem lies under the fractional optimization class 13, due to absence of the decision variables. Mainly, we aim to solve a problem like

$$\max_{\mathbf{x}\in\mathcal{C}} \frac{f(\mathbf{x})}{g(\mathbf{x})} \tag{13}$$

for suitable f and g.

A feasible problem can be solved by finding the unique zero of $F(\lambda)$ where a point $\mathbf{x} \in \mathcal{C}$ solves (13) if and only if $\mathbf{x}^* = \arg\max_{\mathbf{x}\in\mathcal{C}}\{f(\mathbf{x}^*) - \lambda^* g(\mathbf{x}^*)\}$,with λ^* being the unique

Algorithm 2 EE maximization for $M > 1$

if Problem feasible **then**
  $i = 0$
  Pick any $\mathbf{p}_k^{(0)}, \mathbf{p}_m^{(0)} \in \mathcal{P}$.
  repeat
    $i = i + 1$
    Solve (6) with parameters $a_k^{(i)}$, $b_m^{(i)}$ and $b_k^{(i)}$, $a_m^{(i)}$
    Set $p_k^{(i)} = 2^{q_k^{(i)}}$, $p_m^{(i)} = 2^{q_m^{(i)}}$ where $q_k^{(i)}, q_m^{(i)} = \arg\max \tilde{\eta}_i$
    Set $\tilde{\gamma}_k^{(i)} = \gamma_k(\mathbf{p_k}^{(i)})$ and $\tilde{\gamma}_m^{(i)} = \gamma_m(\mathbf{p_m}^{(i)})$
    Update $a_k^{(i)}$, $b_m^{(i)}$ and $b_k^{(i)}$, $a_m^{(i)}$
  until convergence
end if

Algorithm 3 Dinkelbach's algorithm

$\epsilon > 0, \lambda = 0$
repeat
  $\mathbf{x}^* = \arg\max_{\mathbf{x}\in C}\{f(\mathbf{x}) - \lambda g(\mathbf{x})\}$
  $F = f(\mathbf{x}^*) - \lambda g(\mathbf{x}^*)$
  $\lambda = f(\mathbf{x}^*)/g(\mathbf{x}^*)$
until $F \leq \epsilon$

zero of $F(\lambda) = \max_{\mathbf{x}\in\mathcal{C}}\{f(\mathbf{x}) - \lambda g(\mathbf{x})\}$. For this, we use Dinkelbach's algorithm [12] that is presented in algorithm 3 for GEE to solve one convex problem in each iteration such as $f(\mathbf{x})$ and $g(\mathbf{x})$ are concave and convex respectively. However, in our case the feasible set is convex yet the numerator of (6) is non-concave thus we use sequential convex programming approach such as

$$\log_2(1+\gamma) \geq a \log_2 \gamma + b. \tag{14}$$

$$a = \frac{\overline{\gamma}}{1+\overline{\gamma}}, b = \log_2(1+\overline{\gamma}) - \frac{\overline{\gamma}}{1+\overline{\gamma}} \log_2 \overline{\gamma} \tag{15}$$

The complete solution procedure is summarized in algorithm 2.

VI. Simulations and Results

Stochastic geometry models view a network as a realization of a spatial point random process. This framework is an essential tool to analyse system performance, specifically spectral efficiency, coverage, outage, ... etc [13], [14]. In this work, a standard homogeneous Poisson point process (PPP) distribution is used to determine the number and locations of the cellular users and of the D2MD transmitters and receivers, with density λ. Moreover, the received signal or interference power is assumed to vary due to the path loss resulting from the random spatial distribution. In particular, the channel quality between a transmitter at $y \in \mathbb{R}^2$ is

$$P_r = P_t \cdot \left(1 + \left|\frac{y}{d_0}\right|^{\alpha}\right) \tag{16}$$

TABLE I: System Parameters.

PARAMETER	VALUES
bandwidth	$10e^8$ Hz
cell size	500m
Number of D2D groups	4
Number of CUE users	$4, 6, 8$
Split factor	$2, 3, 4$
Re-use factor	2
Network density (λ)	250
Minimum transmission rate	0.1 bit/Hz/s
Minimum D2MD total rate	0.5 bit/Hz/s
Maximum transmission powers	$[-5, 25]$ dBm
Noise power density N_0	-100 dBm/Hz
Number of Iterations	200
Circuit Power	10 dBm
Path loss exponent	2.5

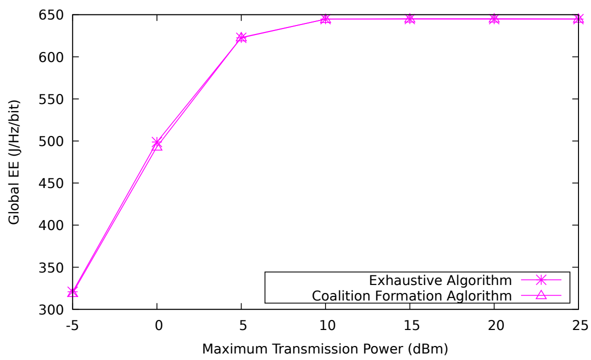

Fig. 2: GEE vs. Transmission Power for Greedy and KNN.

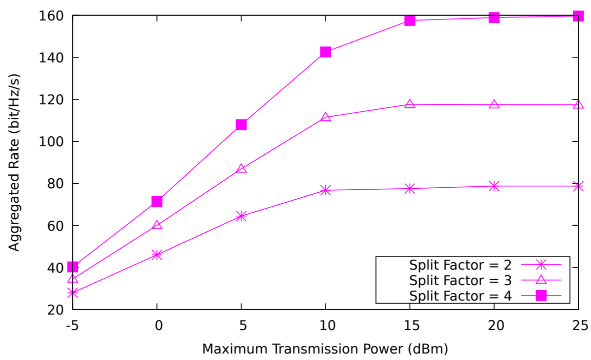

Fig. 5: Global Rate vs. Transmission Power for KNN.

where P_r is the received power, P_t is the transmitted power, d_0 is a reference distance (equal to 100 m in our case), and α is the path loss exponent. On the one hand CUE, the users with the best channel quality are chosen to share their RB with D2MD groups [15]. This will provides us with better insights on the influence of D2MD users, since shared channel quality is ignored. In addition, CUEs with poor channel qualities are expected to prefer the D2MD communication mode seeking for better performance. On the other hand, the formation of D2MD groups formation and the selection of the head cluster were done in a centralized way by applying two clustering techniques detailed below. For the numerical experiments, we used MATLAB and CVX [16] for the implementation of the algorithms. The parameters used for the numerical results reported here are listed in Table I and are similar to typical

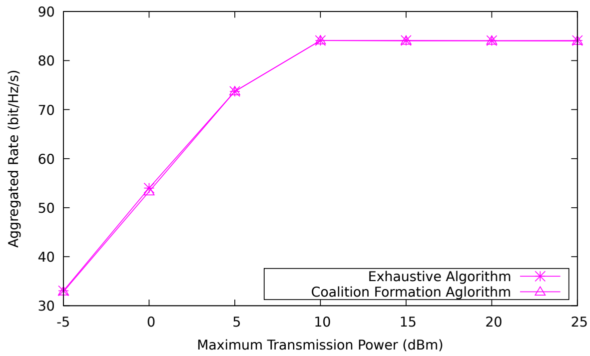

Fig. 3: Global Rate vs. Transmission Power for Greedy and KNN.

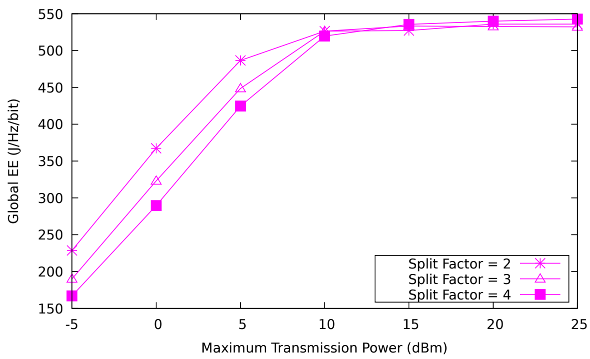

Fig. 4: GEE vs. Transmission Power for KNN.

values used in other works [17], [18], [19]. As stated above, in this paper, we focus on two clustering algorithms:

1) **K-Nearest Neighbour (KNN)** is a clustering technique which permits to classify users into a number K disjoint homogeneous groups. The K head clusters/transmitters are randomly selected among a set of points drawn from a homogeneous Poisson point process $\mathcal{S}$, with density λ. The rest of users/points in $\mathcal{S}$ are considered as potential receivers assigned to the closest group head. Finally, only the groups that reach the target size $|\mathcal{D}_k|$ are admitted.
2) **Distance limited (DL)** is similar to KNN in that we specify in advance the number of clusters K to be formed. However, the distance between transmitter/receivers is explicitly monitored with a new parameter called ($d_{\max}$), specified as a fraction of the cell radius. Here, all users located in a radius of $d_{\max}$ of some of the k head clusters are retained as receivers. This means that DL can form heterogeneous groups with unicast and multicast communication simultaneously.

A. *Optimality of Coalition formation algorithm*

To assess the performance quality of the merge and split rules, we compare it with a greedy algorithm which evaluates all the possible pairings between the available CUE and D2MD via algorithm 2 to select the CUE' and $D2MD'$ pair that achieves the highest GEE. However, the selection process

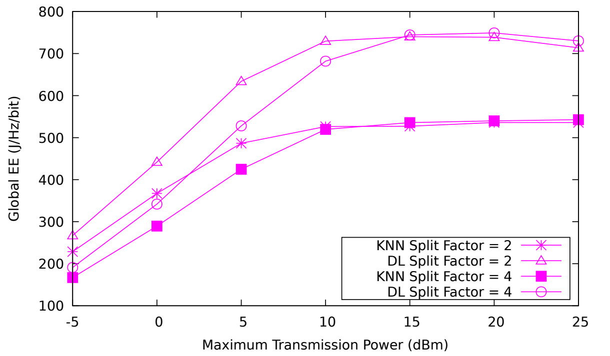

Fig. 6: GEE vs. Transmission Power for DL vs. KNN.

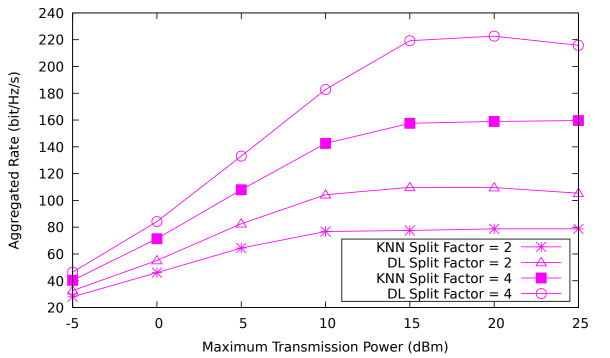

Fig. 7: Aggregated Rate vs. Transmission Power for DL vs. KNN.

may be affected if the clusters are heterogeneous, i.e., if each one has different number of receivers. This is because groups with more receivers achieve higher rate with low power consumption, which in turn increases GEE. Therefore, we use KNN with 5 groups of size equal to 3 and minimum rate per channel equal to 0.1 bit/Hz/s. Since the greedy algorithm is costly in terms of computing time, the reuse and split factors are set to $r = s = 1$ while the maximum transmission power per channel varies in the range $[-5, 25]$ dBm. Figures 2 and 3 show global EE and aggregated rate respectively. Clearly, the coalitional game approach performs close to optimal yet with much lower complexity.

B. Feasibility, Rate and GEE Analysis

In this work, the test cases were designed to ensure a sufficient similarity between the DL and KNN clustering techniques in order to provide a fair and clear comparison. Here, the minimum rate per channel is set to 0.1 bit/Hz/s to avoid the coexistence of poor and highly good channels hence, this will not be useful for D2MD and CUE and only will lead to higher power consumption. The split factor is always fixed to $s = 2$ while r is set to $2, 3, 4$, with the number of groups equal to 4, and CUE equal to $4, 6, 8$ respectively. Network density $\lambda = 250$ and the distance ratio is $1/8$ for DL to limit the maximum average distance between a HC and the receivers to 50 m approx. as for KNN.

a) Problem Feasibility: was evaluated in the previously detailed scenarios where D2MD groups are allowed to distribute their total transmission rate (minimum set to 0.5 bit/Hz/s) and total transmission power (maximum is in the range of $[-5, 25]$ dBm). The results were averaged over 200 feasible cases. In the first case, the average number of non-feasible problem instances is 7, where this decreases to 2 as more resources are available to share for KNN clusters. Differently, the average number increases for DL clustering technique to rise from 2 to 9.

b) Sum-Rate Capacity and EE: were investigated over a wide range of available transmission powers, $[-5, 25]$ dBm and averaging 200 random feasible test cases. Figures 4 and 5 show that both the rate and the GEE increase as we increase the users' transmission budget, with the KNN clustering technique. Similarly, the behaviour holds when we replicate the same scenarios for DL, as shown in Figure 6,7. But we notice that DL achieved better performance, for, as previously explained, larger groups means higher data rate and lower power consumption. Generally, we observe that GEE and the aggregated rate are continuously increasing till both reach a saturation point where no further improvement is possible. However, the split factor affects differently the EE and the rate, since in the first case as more resources a D2MD group have the less EE attains. This behaviour is reversed only in the case that greater power budget is used. In the second case, the rate keeps increasing as more resources are available.

c) Discussion: Obviously, clustering techniques have no major impact on network performance. In fact, energy efficiency and aggregated rate curves have similar shape either with KNN or DL. However, the obtained results can be enhanced under certain conditions as in DL, where the number of receivers is not the same for all the groups, i.e., heterogeneous clusters and support the coexistence of uni and multi-cast communication topology. To this point, it is worth to mention that DL is not sensitive to λ. However, the split and reuse factors have different effects on EE and aggregated rate, where more resources always lead to higher data rate. That is not the case of EE. Here, better EE can be achieved with less amount of resources. To conclude, the system will always reach a peak point where no further enhancement is possible due to interference power.

VII. Conclusion

In this paper, we modelled the joint resources and power allocation as mixed integer non-linear problem (MINLP) with reuse of resources. Differently from exiting work in the research area, we investigate a two-stages semi-distributed solution approach for the NP-hard problem at hand. In the first stage, we use overlapping coalition formation game model to solve resource allocation problem subject to reuse and split factors while considering maximum transmission and minimum power constraints. In the second stage, the problem becomes a classic power control optimization and falls within the framework of fractional programming, so it can be optimally solved using a simple iterative algorithm. The combined framework of game theory and optimization result in performance close to optimal. For future work, it will be interesting to study different RB sharing scenarios and to identify the best configuration in each case. In addition, it will be of high interest to compare centralized and fully or semi distributed solutions and their impact on individual users EE and rate.

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Appendix

The inequalities

$$\frac{h_j p_j}{\sigma^2 + \sum_{i \neq j} p_i h_{i,j}} \geq \underline{\gamma}_j$$

for $j = 0, \ldots, K$ can be equivalently written with matrix notation as

$$(I - W)\mathbf{p} \geq \underline{\mathbf{s}},$$

where $\mathbf{p}$ is a feasible power vector and $\underline{\mathbf{s}}$ is defined as in the statement of the theorem. If a vector $\mathbf{p}'$ meets the target rates and is such that $p_i' \geq \overline{p}_k$ for some k, then

$$\frac{h_k p_k}{\sigma^2 + \sum_{i \neq j} p_i' h_{i,j}} < \mathsf{SINR}_k(\overline{\mathbf{p}})$$

for any $p_k \leq \overline{p}_k$. Thus there is no power $p_k \leq \overline{p}_k$ such that $\gamma_k = \mathsf{SINR}_k(\overline{\mathbf{p}})$. If the spectral radius of W, which is irreducible and nonnegative, is not less than one, then there does not exist a power vector such that $\gamma_k = \mathsf{SINR}_k(\overline{\mathbf{p}})$.

Note that

$$\overline{\mathbf{p}} = \sum_{i=0}^{\infty} W^i \underline{\mathbf{s}}$$

is then a feasible solution to the power allocation problem.

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