Base Station Assisted Neighbor Discovery in Device to Device Systems

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***Abstract*—Neighbor discovery is an essential prerequisite for any device-to-device (D2D) communication. Unlike ad-hoc networks, the base station (BS) in D2D networks may facilitate the neighbor discovery process. However, device-to-BS channel states or device locations are not enough to provide BS with information on the channel quality *between* the devices. Thus, due to the inherent uncertainty of link quality between devices, the BS-assisted neighbor discovery cannot be treated as typical scheduling problem.**

In this paper, we investigate the assisted directional neighbor discovery in D2D networks. We first formulate the scheduling problem as an integer optimization problem that captures the uncertainty. Then we propose a greedy based centralized scheduling to determine directional pilot transmission instances. We also propose a one-way randomized discovery, where we choose the directional transmission probabilities based on two techniques, an intuitive and an optimized methods. Finally, we provide simulation results that assess the performance the schemes.

I. Introduction

The ubiquity of smart mobile devices and the emergence of new localized applications have created new challenges to the traditional structure of mobile networks. One solution that has gained popularity in recent years is device-to-device (D2D) communication [1]. Enabling D2D communication increases the resource reuse, allows the network controller to offload local traffic to D2D links and to offer many proximity-based services. However, setting up and scheduling a D2D link requires that such a link has sufficient channel quality (low attenuation); devices that fulfill this condition and thus can communicate with each other are called "neighbors". To discover its neighbors, a device has to receive pilot signals that verify channel quality between the devices.

5G wireless systems are expected to work, at least partly, in the mm-wave band due to the large available bandwidth and associated high throughput possible there. Due to the high free-space pathloss, directional antennas are required for reasonable range. As a result, *directional* discovery is a necessity, i.e., a device has to determine its neighbors for different beam directions.

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The basic neighbor discovery problem has been addressed extensively in the area of ad hoc networks, i.e., networks without central controllers. Directional neighbor discovery is challenging since successful transmission requires the device to be in the correct transmission state as well as the right directional orientation. D2D networks have an advantage over ad hoc networks in that the Base-station (BS) can be used to manage the communication and the signaling between the devices and perform centralizd computations.

Neighbor discovery in D2D networks with BS has been addressed recently, the main research direction being the integration of D2D neighbor discovery with the current and future standards, e.g., [2], [3], or to incorporate upper layers requirements, e.g., the application layer, with the discovery process [4]. Other papers consider human behavior and social attributes in neighbor discovery, e.g., [5].

In this paper, we consider the basic BS-assisted neighbor discovery problem in D2D networks with directional antennas. We assume that the BS is aware of the probabilistic quality of the links between the devices, possibly through the knowledge of their locations. Note, though, that even when the locations and channel states to the BS of all devices are known, this provides, at best, *partial* information about the quality of the channels *between* devices [5], [6], so that neighbor discovery still needs to be performed. In this work, the BS, using the partial knowledge, can define a superset of neighbor nodes for each device in each direction. Then, through neighbor discovery, devices have to refine this knowledge (i.e., discover their true neighbors). We investigate two techniques for BS-assisted neighbor discovery, the first is based on deterministic resource allocation for pilot signal transmission. The second is a randomized scheme, i.e., devices select the beam directions and transmission states at random; the BS helps in tuning the directional transmission probabilities. In summary, our contributions are as follows:

- We formulate the pilot scheduling as a deterministic integer optimization problem. The objective is to minimize the duration of neighbor discovery and the number of missed detections.
- We develop a greedy scheme to create the pilot schedules that maintains low missed detection.
- We develop a one-way randomized scheme, and propose two methods to set the values of directional transmission probabilities.

The remainder of the paper is organized as follows: in Sec. II we introduce the system model. In Sec. III we formulate the neighbor discovery schedule as an integer optimization program and suggest a greedy scheme to schedule the pilots transmission. In Sec. IV we provide the randomized technique. In Sec. V we present the simulation results.

II. System Model

We consider a BS-assisted synchronized and time slotted D2D network with N quasi-static and half duplex devices [6]. Devices use antenna arrays with beam width ω. To be able to cover its surrounding, each device requires $\Sigma = \lceil \frac{2\pi}{\omega} \rceil$ directions.[1] Let $\theta \in \{1, \ldots, \Sigma\}$ denote a direction. Due to cost and hardware complexity we assume that each device has a single RF chain, and thus nodes can transmit or receive in a single direction at a time.

We also assume that each device i can only communicate with another neighboring device j on only one direction (typically line of sight) denoted by $\theta_{i,j}$. For each device i, let $\mathcal{N}^*_{i,\theta}$ denote the set of devices that i can communicate with effectively in direction θ. Each device is assigned a unique identifier and other devices will recognize it as a neighbor when they receive this identifier. We consider the *collision model* where devices can receive the transmitted identifier in a certain direction, if no other device transmits to them in the same direction, i.e., no other devices interfere with its *discovery*. While this is a conservative model, (e.g., neglecting the possibility of capture), it reflects the basic behavior of neighbor discovery well.

Furthermore, we assume that the BS has probabilistic knowledge about neighbor relations. Assuming a certain channel model, e.g., a break point path loss model [6], for a signal transmitted at device i the received power at device j is given in log scale by

$$Pr_{i,j} = Pt_i - PL(d_{i,j}) + X_{\text{sh}}, \qquad (dBm) \qquad (1)$$

where $Pr_{i,j}$ and Pt_i, is the received power at j and the transmitted power at device i, respectively. $PL(d_{i,j})$ is a deterministic path loss between i and j that are $d_{i,j}$ meters apart, and X_{sh} is shadowing. We assume sufficient diversity (e.g., due to wideband transmission) such that the small-scale fading can be averaged out. In this case, and assuming the BS knows the device locations, it could estimate the probability that two devices are neighbors, $\alpha_{i,j} = \mathbb{P}(Pr_{i,j} \geq P_{\min})$ for given minimum signal level $P_{\min}$.[2] We assume that the BS knows a superset of device neighbors $\mathcal{N}^*_{i,\theta} \subset \mathcal{N}_{i,\theta}$. In this work we ignore the impact of errors in devices location and direction information; they will be considered in our future research.

The goal of the directional neighbor discovery problem is to minimize the time required for each device i to identify all its neighbors $\mathcal{N}^*_i = \cup_\theta \mathcal{N}^*_{i,\theta}$. Finally, for clarity, in this paper we use several indexing methods when we refer to beam directions: (i) double index, e.g., $\theta_{i,j}$ the beam direction that i uses to communicate with j,(ii) single index, e.g., θ_i to represent the beam direction that i uses, and (iii) non indexed, θ for a generic beam direction. Additionally, we refer to the instance when i is a transmitting to j by link (i, j).

III. Fully Centralized Neighbor Discovery

Ideally if the BS knows the exact neighbor relations, it can schedule the pilot transmissions such that for each instance a devices knows apriori the direction where it should steer its beam and the transmission state. This can be viewed as a scheduling problem. However, the problem is different from the typical scheduling in two aspects; (i) each device could be involved in multiple links (multiple neighbor devices), and (ii) with the given the *probabilistic relations*, many of the links do not exist, thus, using dedicated time slots for each link is a waste of resources. In the following we first formulate this scheduling problem as integer program that demonstrates the underlined challenges in such problem; then we provide a greedy scheme based on it.

A. Optimized Neighbor Discovery

We use the standard way to write the scheduling problem for $(i, j),\ j \in \mathcal{N}_i\ \forall i$. However, to account for possible collisions in the shared time slots, we use a cost function $\mathbf{C}$ that penalizes collisions. A reasonable quantity captured by $\mathbf{C}$ could be the number of time slots needed for pilots re-transmissions, and thus collision resolution. Note that this is a random quantity that is difficult to identify exactly, since it depends on the initial schedule, the actual existence

[1] For simplicity of notation, we only consider scanning in azimuth. We furthermore assume that all beams are disjoint, and 2π is an integer multiple of ω.

[2] In Sec. V we use Signal to Noise Ratio (SNR) and thus use $SNR_{\min}$ rather than $P_{\min}$, for given bandwidth and other parameters one can be calculated from the other [6].

of the links and the technique used to schedule the re-transmissions. We suggest a simple form for $\mathbf{C}$ below, after we state the optimization problem.

Let us first define a few binary variables that we use next. The variable $y^{(t)}$ is equal to one if time slot t is used in the schedule, $x_{ij}^{(t)}$ takes the value one if link (i,j) is scheduled in time slot t. $r_{j,\theta}^{(t)}$ takes value one if device j is scheduled to receive from direction θ in time slot t. $\tau_{i,\theta_{ij}}^{(t)}$ takes value one if device i is scheduled to transmit at time t in the direction θ where i can "see" j. Finally, let $\mathcal{I}_{ij}$ be the set of links that *conflict* with (i,j), which are the links due to half duplex assumption, e.g., (j,i), the links due to the directional transmission, e.g., (i,k) if k is in direction other than θ_{ij}, and the links due to the collision model, e.g., (k,j) or (k,u), if $u \in \mathcal{N}_{k,\theta_{kj}}$. Note that the BS generates $\mathcal{I}_{ij}$ based on its *estimate* of device relations.

$$\textbf{OPT-CNT:} \qquad \min \sum_t \mathbf{y}^{(t)} + \beta \mathbf{C}(\boldsymbol{\alpha}, \boldsymbol{\tau}, \boldsymbol{r})$$

$$\text{subject to: } \sum_t x_{ij}^{(t)} \geq 1 \tag{2}$$

$$x_{ij}^{(t)} \leq y^{(t)} \tag{3}$$

$$x_{ij}^{(t)} \leq \tau_{i,\theta}^{(t)} \tag{4}$$

$$x_{ij}^{(t)} \leq r_{i,\theta}^{(t)} \tag{5}$$

$$\sum_{j \notin \{\mathcal{N}_i \setminus \mathcal{N}_{i,\theta}\}} x_{ij}^{(t)} \leq (1 - \tau_{i,\theta}^{(t)})|N| \tag{6}$$

$$\sum_{i \notin \{\mathcal{N}_j \setminus \mathcal{N}_{j,\theta}\}} x_{ij}^{(t)} \leq (1 - r_{j,\theta}^{(t)})|N| \tag{7}$$

$$\tau_{j,\theta}^{(t)} \leq (1 - r_{i,\theta}^{(t)}) \tag{8}$$

$$x_{ij}^{(t)} + \sum_{(u,v) \in \mathcal{I}_{ij}} x_{uv}^{(t)} \leq \gamma \tag{9}$$

$$x_{ij}^{(t)}, r_{i,\theta}^{(t)}, \tau_{i,\theta}^{(t)} \in \{0,1\} \ \forall i \ \forall j \ \forall \theta \forall t \tag{10}$$

where β is a design value that reflects the price of re-transmission. Vectors $\boldsymbol{\alpha}, \boldsymbol{\tau}$ and $\boldsymbol{r}$ contain the values for $\alpha_{ij}, \tau_{i,\theta}^{(t)}, r_{i,\theta}^{(t)}, \forall i, \forall j, \forall \theta, \forall t$. The constraint (2) guarantees that link (i,j) is active at least one time. The constrains in (3), (4) and (5) are coupling arguments. Constraints (6) and (7) guarantee that a device is not active in more than one direction at a time. (8) enforces the half duplex communication. (9) is related to links conflict, note that if $\gamma = 1$, some other constraints are not needed, such as constraint (8). In the remainder of this paper we use $\gamma = 2$, which allows for collision of up to two links, for instance we may schedule (i,j) and (k,j) if $i,k \in \mathcal{N}_{i,\theta}$ in the same time slot. In that case we replace $\mathbf{C}$ with $\tilde{\mathbf{C}}$, where $\tilde{\mathbf{C}}$ is a simple approximation to the expected value of $\mathbf{C}$. In particular, $\tilde{\mathbf{C}}$ is the expected

$\mathcal{L}_o \leftarrow$ Order $\mathcal{L}_{i,\theta}$ based on the values $g_{i,\theta}(\alpha_0)$ (in descending order).
initialize: $T_{\max} = 1$.
for $l = 1 : |\mathcal{L}_o|$ **do**
  $(i,j) \leftarrow \mathcal{L}_o(l)$
  for $t = 1 : T_{\max}$ **do**
    if $\mathcal{I}_{i,j}(\alpha_0) \cap \mathcal{S}_t \bigcup \{(i,j)\} \cap \mathcal{I}_t(\alpha_0) = \emptyset$ **then**
      $c_t = \sum_{k:\{(k,u) \in \mathcal{I}_{i,j} \cap \mathcal{S}_t\}} \alpha_{ij}\alpha_{kj} + \sum_{(k,u) \in \mathcal{S}_t \text{ and } (i,j) \in \mathcal{I}_{k,u}} \alpha_{ku}\alpha_{iu}$
    else
      set $c_t = \infty$
    end if
  end for
  if $c_t \geq 0.5 \ \forall t \in \{1, ..., T_{\max}\}$ **then**
    $T_{\max} \leftarrow T_{\max} + 1$, $\mathcal{S}_{T_{\max}} \leftarrow \{(i,j)\}$
  else
    $t^* \leftarrow \arg\min_t c_t$, $\mathcal{S}_{t^*} \leftarrow \mathcal{S}_{t^*} \cup \{(i,j)\}$
  end if
end for

Algorithm 1: Greedy Centralized Neighbor Discovery Algorithm

number of collisions, and can be given by

$$\tilde{\mathbf{C}}(\boldsymbol{\alpha}, \boldsymbol{\tau}, \boldsymbol{r}) = \sum_{t,j,\theta} \sum_{i,k \in \mathcal{N}_{j,\theta}} \alpha_{ij}\alpha_{kj} \tau_{i,\theta_{ij}}^{(t)} \tau_{i,\theta_{kj}}^{(t)} r_{j,\theta}^{(t)},$$

which can be derived by taking the expected value of the sum of collisions' indicator functions. Note that **OPT-CNT** is a generalization of the graph coloring problem, in particular, assuming that each (i,j) is a vertex and when $\beta = 0$ and $\gamma = 1$ then the problem reduces to the classical graph coloring problem, which is known to be NP-hard. We do not provide further details about the hardness of the above problem, rather we next provide a greedy scheme that produces a desirable schedule.

B. Greedy Centralized Schedule

The idea of the scheme is to reduce the probability of collision by protecting links that have high probability to exist, larger than a design constant $\alpha_0 \in [0,1)$, by providing dedicated time slots if required, and allow a minimal collision probability for links that are less likely to exist. Note that $\alpha_0 = 0$ means that we assume that all the links exist and protect all of them equally. Once a link (i,j) is scheduled the scheme greedily schedules all the links in the same direction if possible, i.e., (i,u) $u \in \mathcal{N}_{i,\theta_{i,j}}$. Let $\mathcal{L}_{i,\theta}$ be the set of links (i,j) $\forall j \in \mathcal{N}_{i,\theta}$. We define $g_{i,\theta}(\alpha_0)$ as the number of links in $\mathcal{L}_{i,\theta}$ that exist with probability greater than α_0, i.e., $g_{i,\theta}(\alpha_0) = \{\#(i,j) | j \in \mathcal{N}_{i,\theta}, \alpha_{i,j} > \alpha_0\}$. We use $\mathcal{S}_t$ to denote the set of links that are scheduled in t.

In Algorithm 1, for given α_0, we first sort *the links* by ordering the sets $\mathcal{L}_{i,\theta}$ in decreasing order of $g_{i,\theta}(\alpha_0)$ $\forall i$ $\forall\theta$. Note that to activate (u,k) along with (i,j) we require $(u,k) \notin \mathcal{I}_{i,j}$ if $\alpha_{i,j} \geq \alpha_0$ and $(u,k) \notin \tilde{\mathcal{I}}_{i,j}$ if $\alpha_{i,j} < \alpha_0$, where $\tilde{\mathcal{I}}_{i,j}$ is the subset of links in $\mathcal{I}_{i,j}$ with relaxed collision model condition, in particular, in addition to other conditions which are as well represented by the constraints (6)-(9), $(k,u) \in \tilde{\mathcal{I}}_{i,j}$ if $\alpha_{k,u} \geq \alpha_0$. We use $\mathcal{I}_{i,j}(\alpha_0)$ to represent the appropriate set for (i,j), i.e., $\mathcal{I}_{i,j}(\alpha_0) = \mathcal{I}_{i,j}$ if $\alpha_{i,j} \geq \alpha_0$ and $\mathcal{I}_{i,j}(\alpha_0) = \tilde{\mathcal{I}}_{i,j}$ otherwise. We further use $\mathcal{I}_t(\alpha_0)$ to denote the union of all $\mathcal{I}_{u,k}(\alpha_0)$ for all $(u,k) \in \mathcal{S}_t$.

A link is added to the time slot t^* that has the least number of expected collisions, c_{t^*}, with the condition that the link that exists with high probability receives no interference.

IV. Assisted Randomized Schemes

Randomized neighbor discovery schemes are popular for ad hoc network, in the absence of a central controller. Nevertheless, the schemes can be useful when the network has uncertainty [7]. Therefore, it is interesting to study and compare the performance of neighbor discovery schemes when a BS is present.

In a one-way randomized scheme, [7], each device either transmits or listens with fixed probability. Let Θ_i denote the direction device i chooses at a given instant, then device i randomly selects a direction θ with some probability $\mathbb{P}(\Theta_i = \theta) = q_{i,\theta}$, and then chooses to transmits,(i.e., announces its identifier), in that direction with some probability $\mathbb{P}(X_i = 1 \mid \Theta_i = \theta) = p_{i,\theta}$ or listens with probability $(1-p_{i,\theta})$, where X_i denotes the transmission state of i which is one if it is transmitting and zero otherwise. Note that $\sum_{\theta\in\{1,\ldots,\Sigma\}} q_{i,\theta} = 1$. With assistance of the BS, our goal is to determine the parameters p_{i,θ_i} and q_{i,θ_i} for all θ_i and i.

Let $\mathcal{D}_{j,i}$ denote the event of device i detecting device j, i.e., i receives the device j's identifier, hence the order of the subscripts. For device i to successfully discover device j, three conditions must be satisfied: (1) Device j needs to transmit in direction $\Theta_j = \theta_{j,i}$ which occurs with probability $p_{j,\theta_{j,i}} q_{j,\theta_{j,i}}$. (2) Device i has to listen in direction $\Theta_i = \theta_{i,j}$ that happens with probability $(1 - p_{i,\theta_{i,j}}) q_{i,\theta_{i,j}}$. (3) No other device $k \in \mathcal{N}_{i,\theta_{j,i}}$ transmits in direction that i receives j, i.e., $\theta_{k,i}$. Let $k \not\rightarrow \mathcal{D}_{i,j}$ denotes the latter event that k does not interfere with i discovering j. Clearly, $\mathbb{P}(k \not\rightarrow \mathcal{D}_{j,i}) = (1 - p_{k,\theta_{k,i}} q_{k,\theta_{k,i}})$. Thus, as derived also in [8], the probability of successful discovery is given by

$$\mathbb{P}(\mathcal{D}_{j,i}) = p_{j,\theta_{j,i}} q_{j,\theta_{j,i}} (1 - p_{i,\theta_{i,j}}) q_{i,\theta_{i,j}} \times \prod_{k\in\mathcal{N}_{i,\theta_{j,i}}} (1 - p_{k,\theta_{k,i}} q_{k,\theta_{k,i}}) \qquad (11)$$

In the above we did not consider the probability that a link exists when calculating the probability of success. In this paper, for simplicity we consider that $\alpha_{ij} = 1$ for the randomized scheme. In the following we provide two methods to choose $p_{i,\theta}$ and $q_{i,\theta}$. The first is based on an intuitive rule, while in the second the choice of $p_{i,\theta}$ and $q_{i,\theta}$ is based on the solution of an optimization problem.

A. Intuitive Method

Based on an earlier result, [9], with uniform distribution of devices, the transmission probability is found to be inversely proportional to the number of neighbors. We set

$$p_{i,\theta} = \frac{1}{N_{i,\theta} + 1}$$

where $N_{i,\theta} = |\mathcal{N}_{i,\theta}|$. In addition

$$q_{i,\theta} = \frac{N_{i,\theta}}{N_i}$$

where $N_i = \sum_\theta N_{i,\theta}$. The values of $p_{i,\theta}$ and $q_{i,\theta}$ are intuitive, since a device transmits with probability, $p_{i,\theta} \times q_{i,\theta}$, with inverse proportionality to the total number of neighbors N_i, and steers its beam to θ with proportionality to the number of neighbors in that direction. We refer to method where devices adopt these probabilities as the *intuitive random scheme*.

B. Optimized Method

One method could be through minimizing the discovery time. Instead we focus here on maximizing the minimum probability of success, for two reasons, first modeling the discovery time and analyzing it is complicated, and second both quantities are related [7]. Thus, the objective function is

$$\max_{\mathbf{p},\mathbf{q}} \min_{i,j} \mathbb{P}(\mathcal{D}_{j,i}). \qquad (12)$$

where $\mathbf{p}$ and $\mathbf{q}$ are all directional transmission probabilities. In contrast to [7], we here focus on providing a simple method that is tractable for large networks.

The Algorithm: We propose the following algorithm to solve (12): The central controller starts by considering an initialization point in $\mathbf{p}$ and $\mathbf{q}$ space. Then, on each iteration, it randomly chooses a device i and tries to find the optimal parameters p_i and q_i given the fixed parameters of other devices. Specifically, for device i, the central controller computes the following parameters at each angle θ_i:

$$T_i(\theta_i) = \min_{j\in\mathcal{N}_{i,\theta_i}} q_{j,\theta_j} \times \mathbb{P}(\mathcal{D}_{i,j} \mid \Theta_j = \theta_{j,i}, \Theta_i = \theta_{i,j}, X_i = 1) \qquad (13)$$

$$R_i(\theta_i) = \min_{j\in\mathcal{N}_{i,\theta_i}} \mathbb{P}(\mathcal{D}_{j,i} \mid \Theta_i = \theta_{i,j}, X_i = 0) \qquad (14)$$

$$H_i(\theta_i) = \min_{j \in \mathcal{N}_{i,\theta_i}} \min_{k \in \mathcal{N}_{j,\theta_j}} q_{j,\theta_j}(1 - p_{j,\theta_j}) \times \mathbb{P}(\mathcal{D}_{k,j} \mid \Theta_j = \theta_{j,i}, X_j = 0, i \not\to \mathcal{D}_{k,j}) \quad (15)$$

Let us briefly discuss the implication of these quantities: $T_i(\theta_i)$ is the minimum probability of discovery when i transmits in direction θ_i. $R_i(\theta_i)$ is the minimum discovering probability when i listens in direction θ_i, and $H_i(\theta_i)$ is the minimum probability of discovery of neighbors of i when i is not interfering in direction θ_i. Note that all of these quantities are probabilities of success that exclude the probability of transmission and directing the beam of device i. For clarity, let us arrange these parameters in the following table format:

$$\begin{matrix} T_i(1) & R_i(1) & H_i(1) \\ T_i(2) & R_i(2) & H_i(2) \\ \vdots & \vdots & \vdots \\ T_i(\Sigma) & R_i(\Sigma) & H_i(\Sigma) \end{matrix} \quad (16)$$

Then our goal is to choose the values of p_{i,θ_i} and q_{i,θ_i} to solve (12). That is, the central controller solves the following optimization problem:

$$\begin{aligned} \textbf{OPT-STEP:} \ & \max_{\mathbf{p}_i, \mathbf{q}_i} \ a \\ \text{subject to:} \ & q_{i,\theta'} p_{i,\theta'} T_i(\theta) \geq a, \ \forall \theta \\ & q_{i,\theta}(1 - p_{i,\theta}) R_i(\theta) \geq a, \ \forall \theta \\ & (1 - p_{i,\theta'} q_{i,\theta'}) H_i(\theta) \geq a, \ \forall \theta \\ & \sum_{\theta} q_{i,\theta} = 1 \\ & q_{i,\theta}, p_{i,\theta} \in [0, 1], \ \forall \theta \end{aligned}$$

The subscripted vectors $\mathbf{p}_i$, $\mathbf{q}_i$ are the transmission and beam directing probabilities of device i. Evidently, **OPT-STEP** maximizes the minimum of $\mathbb{P}(\mathcal{D}_{i,j})$ for all $j \in \mathcal{N}_i$ and θ_i without decreasing the discovery probability of other devices. Fortunately, **OPT-STEP** is a well-behaved, though non-concave, optimization for which we can offer a fast iterative algorithm that can find a solution. We require the following lemmas in deriving the algorithm.

Lemma 1. *There exists a solution such that for any* $\theta \in \{1, \ldots, \Sigma\}$, $q_{i,\theta} p_{i,\theta} T_i(\theta) \leq q_{i,\theta}(1 - p_{i,\theta}) R_i(\theta)$.

Proof. Assume not, i.e., $q_{i,\theta} p_{i,\theta} T_i(\theta) > q_{i,\theta}(1 - p_{i,\theta}) R_i(\theta)$. Then we can simply decrease $p_{i,\theta}$ to have $q_{i,\theta} p_{i,\theta} T_i(\theta) = q_{i,\theta}(1 - p_{i,\theta}) R_i(\theta)$. This way, we increase the minimum of the probabilities of successfully transmitting to and receiving from j. Note that this also increases $(1 - q_{i,\theta} p_{i,\theta}) H_i(\theta)$ and thus does not affect the solution. □

Lemma 2. *There exists a solution such that for any* $\theta \in \{1, \ldots, \Sigma\}$, $q_{i,\theta} p_{i,\theta} T_i(\theta) \leq (1 - p_{i,\theta} q_{i,\theta}) H_i(\theta)$.

Proof. The proof is similar to above and omitted for brevity. □

Clearly, the lemmas above do not specify the solution, rather, in the following, we use them to gradually improve the value of the objective in (12) starting from a feasible point.

It is easy to see that a solution exists which satisfies both events, i.e., $\theta \in \{1, \ldots, \Sigma\}$, $q_{i,\theta} p_{i,\theta} T_i(\theta) \leq q_{i,\theta}(1 - p_{i,\theta}) R_i(\theta)$ and $q_{i,\theta} p_{i,\theta} T_i(\theta) \leq (1 - p_{i,\theta} q_{i,\theta}) H_i(\theta)$. This can be accomplished by simply decreasing $p_{i,\theta}$ such that $q_{i,\theta} p_{i,\theta} T_i(\theta)$ becomes equal to the minimum of the two other values.

Given the above observations, only one of the following two cases can happen:

- case 1) $q_{i,\theta} p_{i,\theta} T_i(\theta) = q_{i,\theta}(1 - p_{i,\theta}) R_i(\theta) < (1 - q_{i,\theta} p_{i,\theta}) H_i(\theta)$.
- case 2) $q_{i,\theta} p_{i,\theta} T_i(\theta) = (1 - q_{i,\theta} p_{i,\theta}) H_i(\theta) \leq q_{i,\theta}(1 - p_{i,\theta}) R_i(\theta)$.

Note that if $q_{i,\theta} p_{i,\theta} T_i(\theta)$ was strictly less than the other two values, we can make it equal to the minimum of the two by increasing $p_{i,\theta}$. Further, recall that $p_{i,\theta}$'s are independent for different θ, while $q_{i,\theta}$'s are correlated as they sum up to one.

We can decide whether we are in the first or the second case based on the ratio $\frac{H_i(\theta)}{R_i(\theta)}$. Specifically, if $\frac{H_i(\theta)}{R_i(\theta)} > \frac{q_{i,\theta} - p_{i,\theta} q_{i,\theta}}{1 - p_{i,\theta} q_{i,\theta}}$ it is the case one, and it is the second case otherwise.

Starting with case 2, we have:

$$p_{i,\theta} q_{i,\theta} = \frac{H_i(\theta)}{H_i(\theta) + T_i(\theta)}. \quad (17)$$

Inserting (17) into the bound on the ratio $\frac{H_i(\theta)}{R_i(\theta)}$, we get the following lower bound on the value of $q_{i,\theta}$

$$q_{i,\theta} \geq \frac{H_i(\theta)}{R_i(\theta)} \frac{T_i(\theta)}{H_i(\theta) + T_i(\theta)} + \frac{H_i(\theta)}{H_i(\theta) + T_i(\theta)}. \quad (18)$$

Notice that increasing $q_{i,\theta}$ more than the bound (18) in the second case, is a waste of resources as device i looses the chance to look more in other directions and will not increase the discovery probability as $p_{i,\theta} q_{i,\theta}$ is fixed. Thus, we set

$$q_{i,\theta} = \frac{H_i(\theta)}{R_i(\theta)} \frac{T_i(\theta)}{H_i(\theta) + T_i(\theta)} + \frac{H_i(\theta)}{H_i(\theta) + T_i(\theta)}. \quad (19)$$

from which by inserting into (17) we get

$$p_{i,\theta} = \frac{R_i(\theta)}{R_i(\theta) + T_i(\theta)}. \quad (20)$$

Going back to case 1, it is easy to check that $p_{i,\theta}$ takes equal value. This is indeed intuitive: The probability of transmitting in direction θ_i is the ratio of probability of being discovered and the sum of the probabilities of discovering and being discovered.

Now let us proceed to compute the probabilities $q_{i,\theta}$ for the first case. Define $\mathcal{C}_2$ to be the set of

while stop-condition **do**
  Make some ordering of the devices Π
  for j = 1:N **do**
    $i = \Pi(j)$
    Make the table (16) for device i
    set $p_{i,\theta}$ according to (20), $\forall\theta$
    set $\mathcal{C}_1 = \{1, \ldots, \Sigma\}, \mathcal{C}_2 = \emptyset$
    repeat
      set $q_{i,\theta}$ according to (21) $\forall\theta \in \mathcal{C}_1$
      update $\mathcal{C}_2 = \{\theta : \frac{H_i(\theta)}{R_i(\theta)} \le \frac{q_{i,\theta} - p_{i,\theta} q_{i,\theta}}{1 - p_{i,\theta} q_{i,\theta}}\}$
      update $\mathcal{C}_1 = \{1, \ldots, \Sigma\} \setminus \mathcal{C}_2$
      set $q_{i,\theta}$ according to (19) $\forall\theta \in \mathcal{C}_2$
    until $\mathcal{C}_1, \mathcal{C}_2$ remain unchanged
  end for
end while

Algorithm 2: Iterative Optimized Neighbor Discovery Algorithm

all direction indices for which the case 2 happens. Accordingly, we can define $\mathcal{C}_1 = \{1, \ldots, \Sigma\} \setminus \mathcal{C}_2$.

Observe that the cost function does not benefit from having different values $q_{i,\theta} p_{i,\theta} T_i(\theta)$ on different directions θ as it can increase the lower values by aiming toward them more. Thus, for $\theta \in \mathcal{C}_1$, we set

$$q_{i,\theta} p_{i,\theta} T_i(\theta) = t, \ \forall\ \theta \in \mathcal{C}_1$$

Then,

$$q_{i,\theta} = \frac{1 - \sum_{\theta' \in \mathcal{C}_2} q_{i,\theta'}}{1 + \sum_{\theta' \in \mathcal{C}_1, \theta' \neq \theta,} \frac{p_{i,\theta} T_i(\theta)}{p_{i,\theta'} T_i(\theta')}}, \ \forall\ \theta \in \mathcal{C}_1. \quad (21)$$

Finally, the arbiter of determining which case each direction θ belongs to is the comparison with the bound (18). Algorithm 2 summarizes the discovery method.

Clearly, the algorithm converges as each step either increases the cost function (12) or leaves it unchanged. The strength of the algorithm also lies in the fact that it converges very quickly, as each epoch of iterating over all devices requires a number of computations linear in the number of devices times number of directions, i.e., $N\Sigma$. We stop the algorithm when the minimum discovery probability is not changing more than a small threshold ϵ.

V. Simulation and Discussion

In this section we study the performance and the efficiency of the schemes. The simulation setup is as follows: we consider a D2D network of N devices that are distributed randomly over a square area with side length of 250 m. Each device can form beams in four directions, i.e., $\Sigma = 4$. We assume that the path-loss follows a break point model with $d_{\text{break}} = 50m$, and propagation exponent $\epsilon_0 = 2$ for $d_{i,j} < d_{\text{break}}$, $\epsilon_1 = 4$

TABLE I
Simulation Parameters

σ_{sh}	6 dB	N	100
Carrier frequency	30 GHz	bandwidth	2 GHz
P_t	10 dBm	$SNR_{\min}$	3 dB

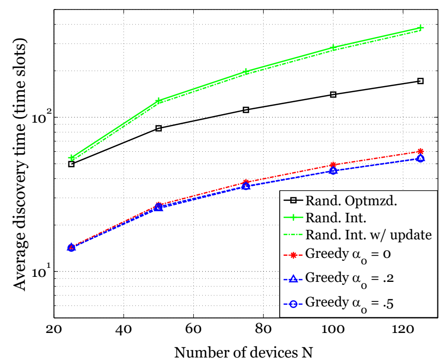

Fig. 1. Discovery time versus number of devices in the network.

for $d_{i,j} \ge d_{\text{break}}$, i.e., for $d_{i,j} \ge d_{\text{break}}$ we have

$$PL(d_{i,j}) = 10 \log \left(\left(\frac{\lambda}{4\pi d_{\text{break}}} \right)^{-\epsilon_0} \left(\frac{d_{\text{break}}}{d_{i,j}} \right)^{-\epsilon_1} \right)$$

where λ is the wavelength [6]. We define i and j to be neighbors if the SNR is greater than or equal to $SNR_{\min}$. We further assume the shadowing X_{sh}, in (1), to have a lognormal distribution, with standard deviation σ_{sh}. Thus, the BS can predict the probability that a link exists. Due to the infinite tail of the lognormal distribution, we assume that the BS considers $j \in \mathcal{N}_{i,\theta}$ if $\mathbb{P}(SNR_{i,j} > SNR_{min}) \ge 0.5\%$. If not stated otherwise we use the parameters summarized in table I.

Fig. 1 shows the average discovery time for various values of N; the simulation is done for 100 realization of device locations and shadowing instances. In the simulation we assumed that the devices need to discover *all* their neighbors. Thus, in the greedy scheme we reschedule the links if collisions occur. However, we do not account for the overhead for communication between the devices and the BS. As per the figure, not surprisingly, the fully centralized greedy scheme significantly outperforms the randomized schemes. We note the small impact of α_0; we will elaborate more on this issue below. Additionally, as can be seen from the figure, the importance of optimizing the $p_{i,\theta}$ and $q_{i,\theta}$ is evident.

As a modification to the random intuitive scheme, we also simulated the case when devices can update their directional transmission probabilities as they discover their neighbors, following the rules in Sec. IV-A. This shows slight improvement to the performance.

For *one* realization of device locations, Fig. 2 shows the normalized number of discoveries over time for the schemes. In this figure, we do not

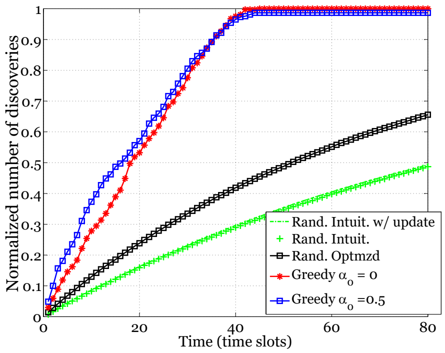

Fig. 2. Normalized total number of discoveries over time, (The time axis is limited to 80 time slots for clarity).

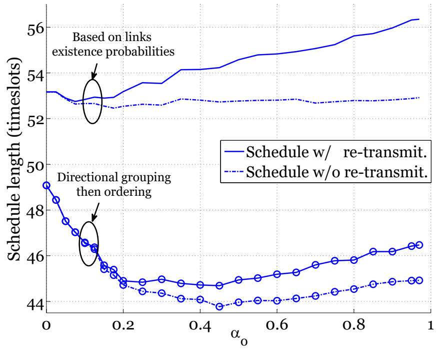

Fig. 3. Impact of α_0 and the sorting technique. Over 100 realizations of devices' locations, the average number of considered links is 2200 links (i.e., links that have prob. exist > 0.5%), and on average 830 links exist (i.e., links that satisfy SNR>1 dB). The average number of missed detection is 6.6 links when $\alpha_0 = 0.5$ for sorting technique shown in Algorithm 1 and 12.4 links for the other technique.

consider re-transmissions. As above, the centralized greedy scheme outperforms the random schemes. In the simulation we used $\alpha_0 = \{0, 0.5\}$. We notice that a small portion of links are not detected due to collisions for $\alpha_0 = 0.5$. Additionally, when $\alpha_0 = 0.5$, we notice fast discoveries in the initial time slots, this is due to the sorting technique discussed earlier.

To understand the impact of α_0 and the sorting technique, Fig. 3 shows the total number of time slots used by the centralized greedy scheme versus α_0, we consider the scenarios with and without re-transmissions. For the latter we notice that as α_0 increases we have small schedule. But large values of α_0 increase the number of links that might collide, thus, the total number of time slots needed to discover all neighbors, i.e., *with* re-transmissions, increases.

In Fig. 3 we also present another sorting technique, in particular, when we sort the links based on their probabilities of existence, so we first schedule the links that exist with high probability and then try to greedily "squeeze in" the ones that exist with low probability. Although this technique sounds reasonable the figure shows the importance of link grouping presented in Sec. III-B.

VI. Conclusion

This paper addresses the problem of BS-assisted directional neighbor discovery in D2D systems. Specifically, assuming a probabilistic neighbor information is apriori known at the BS, and since obtaining an optimum schedule is usually complicated, we propose two types of schemes for neighbor discovery. We first propose a central greedy scheduling scheme that considers the probability of link existence. We then propose a one-way random neighbor discovery, we choose the directional transmission probabilities based on two techniques; the first is an intuitive method, and the second is based on simple optimization of the probability of successful discovery.

The central greedy scheme schedule guarantees no collision for links that exist with probability larger than a certain threshold, α_0, while it allows for controlled probabilistic collision for other links. The simulation results show that it significantly outperforms the randomized schemes. In addition, it shows that α_0 impacts the number of missed detection and the discovery time.

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