Distributed Channel Selection and Randomized Interrogation Algorithms for Large-scale RFID Systems

Amir-Hamed Mohsenian-Rad, *Member, IEEE*, Vahid Shah-Mansouri, *Student Member, IEEE*, Vincent W.S. Wong, *Senior Member, IEEE*, and Robert Schober, *Fellow, IEEE*

***Abstract*— Radio frequency identification (RFID) is an emerging wireless communication technology which allows *objects* to be identified automatically. An RFID system consists of a set of *readers* and several objects, equipped with small and inexpensive computer chips, called *tags*. In a dense RFID system, where several readers are placed together to improve the read rate and correctness, readers and tags can frequently experience packet collision. High probability of collision impairs the benefit of multiple reader deployment and results in misreading. A common approach to avoid collision is to use a distinct frequency channel for interrogation for each reader. Various multi-channel anti-collision protocols have been proposed for RFID readers. However, due to their heuristic nature, most algorithms may not achieve optimal system performance. In this paper, we systematically design two optimization-based distributed channel selection and randomized interrogation algorithms for dense RFID systems. For this purpose, we develop elaborate models for the reader-to-tag and reader-to-reader collision problems. The first algorithm is *fully distributed* and is guaranteed to find a local optimum of a *max-min fair* resource allocation problem for RFID systems. The second algorithm is *semi-distributed* and achieves the *global* optimal system performance. Max-min fair optimality balances the performance and the processing load among readers. Simulation results show that our algorithms have significantly better performance than the previous heuristic algorithms.**

***Index Terms*—Radio frequency identification, randomized multi-channel interrogation, max-min fairness, optimization.**

I. Introduction

Radio frequency identification (RFID) is an emerging wireless technology which allows objects to be identified automatically. An RFID *tag* is a small inexpensive electronic device designed for wireless data transmission. Each tag has a unique ID. It transmits data in response to *interrogation* signals by an RFID *reader*. Multiple readers can connect to a *back-end system* to transfer data for processing or storage. Some of the current RFID applications include supply chain management, inventory checking, access control, and transport payment [1].

RFID tags can be categorized into *passive* and *active*. A passive tag uses backscatter modulation and its transmission power is derived from the signal of the interrogating reader. Passive tags can operate in different frequency bands. Low-frequency tags operate in the 124-135 kHz band and have an operating range of up to 0.5 m. Ultra high frequency tags, which operate at either 860-960 MHz or 2.45 GHz, have a range in the order of 10 m. Active tags require a power source (e.g., a battery) for data transmission and have a larger range (> 100 m). Standardization bodies for RFID include the International Standards Organization and EPCglobal Inc.

In an RFID system with *one* reader and several tags, since the reader and the tags share the same wireless channel, *tag-to-tag* collision can occur when multiple tags transmit signals simultaneously to the same reader. This prevents the reader from recognizing any tag. Various *tag anti-collision* protocols are proposed in [2]. An efficient *Aloha-based* tag anti-collision scheme has also been standardized recently by EPCglobal in [3] where the reader begins each interrogation round by informing all the tags about the frame size. Each tag then chooses a random time slot and transmits its identifier to the reader. If the frame size is large enough, the probability of tag-to-tag collision can be reduced significantly. A measurement study on a single reader RFID system has also been reported in [4]. Algorithms have been proposed to estimate the cardinality of the tag set [5], [6] and to identify the types of tags [7].

In several RFID applications (e.g., for inventory checking in a large-scale warehouse), it is necessary to deploy *several* readers to achieve complete interrogation coverage and also to improve read rate and correctness. In this case, apart from tag collision, *reader-to-tag* and *reader-to-reader* collisions may also occur. Reader-to-tag collision occurs when a tag receives signals of comparable strengths from more than one reader simultaneously. This can cause the tag to respond arbitrarily to the readers, leading to incorrect interrogation. Reader-to-reader collision occurs when a reader, which is in the midst of listening to a tag's reply, receives stronger signals from one or more neighboring readers operating at the same frequency simultaneously. This interference can prevent the reader's receiver from decoding the tag's reply successfully.

In a stationary RFID system with fixed and synchronized readers and a centralized network controller, reader-to-tag and reader-to-reader collisions can be prevented by using a combination of *frequency* and *time division multiple access* [8]. However, in many practical large-scale RFID systems with mobile readers, centralized control is difficult. Therefore, it is of interest to consider *distributed randomized interrogation* schemes such that each reader *randomly* (with probabilities which are *independently* tuned by each reader based on its *local* information) selects the start time of its interrogation rounds and its operating channel to *reduce* the probabilities of reader-to-tag and reader-to-reader collisions. Related algorithms include *naive*, *random*, and *carrier sensing* protocols [9], *distributed interference avoidance* (DIA) algorithm

Manuscript received on January 17, 2009; revised on July 13, 2009 and December 11, 2009; and accepted on December 31, 2009. This work was supported by the Natural Sciences and Engineering Research Council (NSERC) of Canada under grant number STPGP 364962-08. The review of this paper was coordinated by Prof. John Shea. Part of this work was presented at the *IEEE Globecom*, Honolulu, HI, December 2009.

The authors are with the Department of Electrical and Computer Engineering, University of British Columbia, Vancouver, BC, Canada, V6T 1Z4, e-mail: {hamed, vahids, vincentw, schober}@ece.ubc.ca.

with *detect and abort* [10], *slotted listen-before-talk* (S-LBT) [11], *frequency hopping listen-before-talk* (FH-LBT) [12], and *query hit rate* algorithm [13]. However, given the *heuristic* nature of all of these algorithms, some may not be able to fully utilize the potential capacity of RFID systems. This motivates us to study the random access and channel selection problems in RFID systems within an *optimization-based* theoretical framework. Our contributions are as follows:

- We formulate the multi-channel randomized interrogation problem as an optimization problem. Our objective is to achieve *max-min* fair resource allocation among readers by taking into account reader-to-reader and reader-to-tag interference. Max-min fairness balances the performance and the processing load among the readers.
- Two algorithms are proposed to solve the optimization problem. The *fully distributed frequency allocation* algorithm allows each reader to switch its operating channel in each interrogation interval. It works based on the *iterative coordinate ascent* mechanism and is guaranteed to reach a *local* optimal solution of the optimization problem. On the other hand, the *semi-distributed frequency allocation* algorithm allows each reader to use only one channel for a long time. The algorithm is constructed using *generalized Benders decomposition* and guarantees reaching the *global* optimum of the max-min fairness problem.
- Simulation results show that our algorithms have better performance than the previous heuristic reader anti-collision algorithms in terms of the number of correct interrogations and fairness among readers. They also better utilize the available frequency spectrum. They converge fast and are robust to infrequent reader movements.

The rest of this paper is organized as follows. The system model is described in Section II. The proposed algorithms are presented in Sections III and IV. Simulation results ate provided in Section V. The paper is concluded in Section VI.

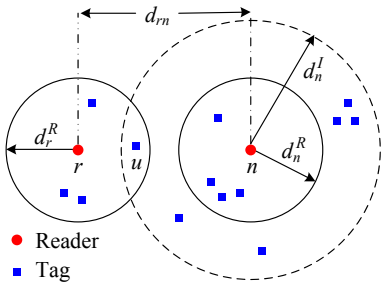
II. System Model

A. Reader Collision Problem

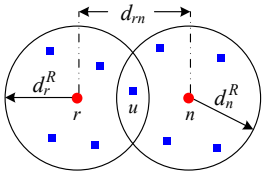
Let $\mathcal{R}$, with size $R=|\mathcal{R}|$, denote the set of all readers. For each $r \in \mathcal{R}$, we define d_r^R as the *read/interrogation range* of reader r. Reader r can collect information only from those tags which are located within its read range. Let d_r^I denote the *interference range*[1] of reader r. Reader r's transmission can interfere the interrogation process of other readers on any tag within its interference range. Two types of reader-to-tag collisions can be distinguished. The first type is shown in Fig. 1(a), where tag u is within the read range of reader r and the interference range of reader n (but *not* within the read range of reader n). If both readers use the same channel and transmit simultaneously, tag u cannot correctly decode the message from its corresponding reader, i.e., reader r. Let $\mathcal{I}_r$ denote the set of readers with their interference area (but not their read area) *overlapping* the read area of reader r. We have

$$\mathcal{I}_r = \{n \ : \ d_r^R + d_n^R < d_{rn} < d_r^R + d_n^I, \ n \in \mathcal{R}\}, \quad (1)$$

[1]We assume that the location of the tags is *not* known prior to interrogations. Therefore, the interference range of the tags are not taken into account and we model the interference using the interference ranges of the readers only.



(a) Type 1: $d_r^R + d_n^R < d_{rn} < d_r^R + d_n^I$



(b) Type 2: $d_r^R + d_n^R \geq d_{rn}$

Fig. 1. Two types of reader-to-tag collisions in an RFID system. Type 1 collision occurs if tag u is within the read range of reader r and the interference range (but not the read range) of reader n. In that case, we have $d_r^R + d_n^R < d_{rn} < d_r^R + d_n^I$. Type 2 reader-to-tag collision occurs if tag u is within the read range of both readers r and n. In that case, we have $d_r^R + d_n^R \geq d_{rn}$. Clearly, Type 1 and Type 2 do not occur at the same time.

where d_{rn} denotes the Euclidean distance between r and n. The first type of reader-to-tag collision if avoided if readers r and n operate at *different frequencies* or *time slots* [13].

The second type of reader-to-tag collision is shown in Fig. 1(b), where tag u is within the read range of *both* readers r and n. Since RFID tags have low functionality and do not have *frequency selectivity* [3], even if readers r and n operate at different channels, tag u cannot decode the interrogation message correctly when both readers transmit simultaneously [13]. Let $\mathcal{S}_r$ denote the set of readers whose read area *overlaps* with that of reader r. We have

$$\mathcal{S}_r = \{n \ : \ d_{rn} < d_r^R + d_n^R, \ n \in \mathcal{R}\}. \quad (2)$$

The second type of reader-to-tag collision can be avoided by having neighboring readers operate at *different time slots*. Notice that having neighboring readers operate at different frequencies *cannot* avoid this type of collision. Also notice that since $d_n^I \geq d_n^R$ for all $n \in \mathcal{R}$, we have

$$\mathcal{I}_r \cap \mathcal{S}_r = \{\}, \qquad \forall r \in \mathcal{R}. \quad (3)$$

On the other hand, reader-to-reader collision occurs when reader n transmits while reader r is receiving another message from tag u (see Fig. 2). Let $\mathcal{V}_r$ denote the set of readers which have reader r within their interference range. That is,

$$\mathcal{V}_r = \{n \ : \ d_{rn} < d_n^I, \ n \in \mathcal{R}\}. \quad (4)$$

Reader-to-reader collision can be avoided if readers operate at *different frequencies* or *time slots*.

From (1)-(4), each reader $r \in \mathcal{R}$ can construct sets $\mathcal{I}_r$, $\mathcal{S}_r$, and $\mathcal{V}_r$ if it can estimate its distance d_{rn} to any other reader $n \neq r$. However, in this paper, we use an alternative and

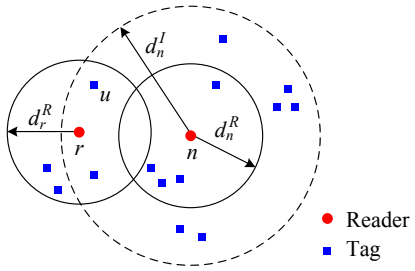


Fig. 2. Reader-to-reader collision in an RFID system.

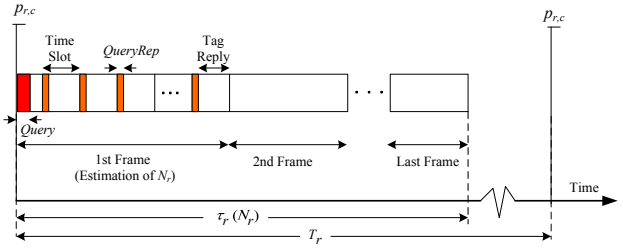


Fig. 3. An interrogation interval, with length T_r time units, for reader r.

simpler practical approach for constructing sets $\mathcal{I}_r$, $\mathcal{S}_r$, and $\mathcal{V}_r$ for each $r \in \mathcal{R}$ which does *not* require the estimation of the distances among readers. Our proposed scheme is based on some simple measurements and employs three orthogonal control channels 1, 2, and 3, which are different from the data channels being used for tag interrogation. Each reader $n \in \mathcal{R}$ periodically transmits HELLO messages over each of the three control channels at predetermined transmit powers Γ_1, Γ_2, and Γ_3. Then, each reader $r \in \mathcal{R}$ keeps track of the HELLO messages it receives over each channel to construct sets $\mathcal{I}_r$, $\mathcal{S}_r$, and $\mathcal{V}_r$. This is done as follows. Each reader $r \in \mathcal{R}$ sets $n \in \mathcal{I}_r$ if and only if it hears HELLO messages from reader n on channel 1, but not on channel 2. It sets $n \in \mathcal{S}_r$ if and only if it hears HELLO messages from reader n on channels 1 and 2. Finally, reader r sets $n \in \mathcal{V}_r$ if and only if it hears HELLO messages from reader n on channel 3. Here, the parameters Γ_1, Γ_2, and Γ_3 are set as the *minimum* required transmit power for decoding HELLO messages sent from another reader within distances $d_r^I + d_r^R$, $2d_r^R$, and d_r^I, respectively. These parameters are fixed, as long as the operating transmit power is fixed for all readers. they can be simply set by the reader manufacturer as pre-determined parameters. As we will explain in Section II-B, each reader $r \in \mathcal{R}$ only needs to estimate sets $\mathcal{I}_r$ and $\mathcal{S}_r$. Therefore, in practice only two control frequency channels will be needed as there is no need to estimate set $\mathcal{V}_r$.

B. RFID Multi-Channel Medium Access Control

Let $\mathcal{C}$, with size $C = |\mathcal{C}|$, denote the set of available orthogonal frequency channels. For multi-channel random access, we assume that the RFID medium access control (MAC) layer complies with the EPCglobal Class-1 Generation-2 (C1G2) standard [14]. Each reader $r \in \mathcal{R}$ attempts to perform the interrogation process every T_r time units. At the beginning of each *interrogation interval* (see Fig. 2), reader r randomly chooses to start an interrogation process over frequency channel $c \in \mathcal{C}$ with *interrogation probability* $p_{r,c} \in [0, 1]$. We have

$$\sum_{c \in \mathcal{C}} p_{r,c} \leq 1, \qquad \forall\ r \in \mathcal{R}. \tag{5}$$

The *channel switching delay* is assumed to be small compared to T_r. Each reader can switch to a new channel in each interrogation interval. The scenario when each reader operates on one channel for a long time is studied in Section IV.

Our proposed channel selection and randomized interrogation algorithms (see Sections III and IV) control reader-to-reader and reader-to-tag collisions, while C1G2 MAC is used to avoid tag-to-tag collision within each read area. According to C1G2 MAC [14], if reader r decides to start an interrogation round, it initiates its 1st *interrogation frame* by broadcasting a *Query* message, which includes the number of time slots within the frame. The rest of the frame is then divided into several small time slots, each starting with a *QueryRep* message to coordinate the timing of sending the reply messages by the tags inside the read area of reader r. Each tag randomly chooses to send its reply back to reader r at one of the available time slots. By the end of the 1st frame, reader r has received the replies from a *subset* of the existing tags. Based on that, it *estimates* the total number of tags inside its read area, denoted by N_r, using a scheme such as [2]. Given the estimate of N_r, reader r initiates more interrogation frames (i.e., 2nd frame, 3rd frame, etc) until it can assure, with a certain confidence, that it has obtained the information from all the tags inside its read area. We denote the duration of an interrogation process by $\tau_r(N_r)$ as shown in Fig. 3.

We assume equal interrogation interval for all readers[2]:

$$T_r = T, \qquad \forall\ r \in \mathcal{R}, \tag{6}$$

where $T > 0$. However, the interrogation intervals of different readers may *not* be synchronized. Therefore, the interrogation process for different readers may *not* start at the same time. We can assume that for each pair of readers $r, n \in \mathcal{R}$, there exists a time difference $\Delta_{r,n}$, called the *asynchronism factor*, between the interrogation intervals of readers r and n. The asynchronism factor $\Delta_{r,n}$ is shown in Fig. 4. Clearly,

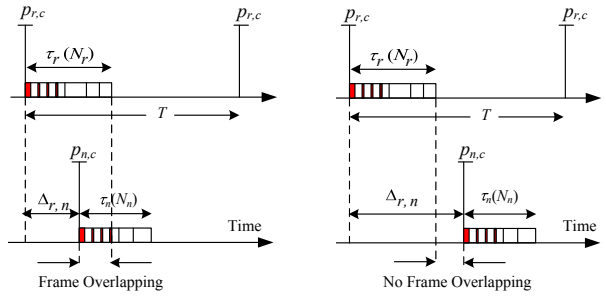
$$-T < \Delta_{r,n} < T, \qquad \forall\ r, n \in \mathcal{R}. \tag{7}$$

Note that $\Delta_{r,n} = -\Delta_{n,r}$. In general, depending on the RFID application, reader r may *not* always be able to estimate $\Delta_{r,n}$. In this paper, unless stated otherwise, we consider the general case, where the asynchronism factors are *not* known.

The asynchronism is beneficial as it allows readers to start their interrogation *not* simultaneously. In Fig. 4, reader r randomly decides to start an interrogation over one of the channels every T time units. If the interrogation of readers r and n have overlap, as in Fig. 4(a), then type 1 or type 2 reader-to-tag collision can occur for $n \in \mathcal{I}_r$ and $n \in \mathcal{S}_r$, respectively. Reader-to-reader collision can also occur if $n \in \mathcal{V}_r$. If the interrogation processes of readers r and n have no overlap, as in Fig. 4(b), then reader collisions will not occur.

Let $\boldsymbol{p} = (p_{r,c},\ \forall\ r \in \mathcal{R},\ c \in \mathcal{C})$ denote the interrogation probability vector. Let $P_r^{\text{succ}}(\boldsymbol{p})$ denote the probability of completing a *successful interrogation interval* by reader $r \in \mathcal{R}$. That is, the probability that reader r starts an interrogation

[2]The assumption in (6) is only for the ease of exposition and can be relaxed by slightly modifying (7), (8), and (10).



(a) $\Delta_{r,n} < \tau_r(N_r)$ (b) $\Delta_{r,n} > \tau_r(N_r)$

Fig. 4. Asynchronism between interrogation intervals for readers r and n: (a) There is a time overlapping. (b) There is no time overlapping.

interval without experiencing either reader-to-reader or reader-to-tag collisions. We can show the following key result.

Theorem 1: Assume that the interrogation interval T is selected large enough to be at least twice as large as the length of any interrogation process among readers. That is, let

$$\max_{r\in\mathcal{R}} \ \tau_r(N_r) \le T/2. \tag{8}$$

In that case, for each reader $r \in \mathcal{R}$, we have

$$\begin{aligned} P_r^{\text{succ}}(\boldsymbol{p}) = &\left(\prod\nolimits_{n\in\mathcal{S}_r}\left(1-\gamma_{r,n}\sum\nolimits_{e\in\mathcal{C}} p_{n,e}\right)\right) \\ &\left(\sum\nolimits_{c\in\mathcal{C}}\ p_{r,c}\left(\prod\nolimits_{m\in\mathcal{I}_r}(1-\gamma_{r,m}\ p_{m,c})\right)\right), \end{aligned} \tag{9}$$

where $\gamma_{r,n}$ denotes the *probability* that the interrogation processes of readers r and n have any time overlapping:[3]

$$\gamma_{r,n} = \frac{\tau_r(N_r)+\tau_n(N_n)}{T}. \tag{10}$$

The proof of Theorem 1 is given in Appendix A. Since $\mathcal{V}_r \subseteq \mathcal{I}_r \cup \mathcal{S}_r$ for each $r \in \mathcal{R}$, if *neither* type 1 *nor* type 2 reader-to-tag collisions occur, then reader-to-reader collision will *not* happen. Thus, set $\mathcal{V}_r$ does not appear in (9). It is easy to verify that for the case that $\tau_r(N_r) > T/2$ for *all* $r \in \mathcal{R}$, we should simply set $\gamma_{r,n} = 1$ for each $r \in \mathcal{R}$ and any $n \in \mathcal{I}_r$.

There are several ways to determine the duration of an interrogation process. In the EPCglobal C1G2 system, we have $\tau_r(N_r) = eN_r\tau^{\text{slot}} \approx 2.72N_r\tau^{\text{slot}}$ for $r \in \mathcal{R}$. Here, τ^{slot} denotes the duration of each time slot. On average, we have $\tau^{\text{slot}} = 850$ μs [3]. Using *enhanced dynamic framed slotted Aloha* [15] with known N_r, we have $\tau_r(N_r) = 3N_r\tau^{\text{slot}}$ for $r \in \mathcal{R}$.

We assume that the readers may move; however, their movement is *infrequent* such that the sets $\mathcal{I}_r$, $\mathcal{S}_r$, and $\mathcal{V}_r$ can be assumed to be fixed for all $r \in \mathcal{R}$ for large intervals of time.

C. Problem Formulation

Let $\mathcal{P}$ denote the *feasible set* for interrogation probabilities:

$$\mathcal{P} = \left\{ \boldsymbol{p}\colon \sum\nolimits_{c\in\mathcal{C}} p_{r,c} \le 1,\ p_{r,c} \in [0,1], \forall\, r \in \mathcal{R}, c \in \mathcal{C} \right\}. \tag{11}$$

In this paper, our goal is to select $\boldsymbol{p} \in \mathcal{P}$ to increase the probability of successful interrogation for all readers to achieve *max-min fairness*. As a result, the processing load is *evenly* distributed among all readers. This also implies max-min fairness for correct interrogation of a tag in *any* of the read areas. Moreover, since higher interrogation success probability implies finishing interrogation faster, by maximizing the minimum interrogation success probability we minimize the maximum interrogation finishing time among readers.

A vector of feasible interrogation probabilities $\boldsymbol{p} \in \mathcal{P}$ is *max-min* fair if any success probability P_r^{succ} cannot increase without decreasing some P_n^{succ} which is smaller than or equal to P_r^{succ}. To obtain max-min fairness, it suffices to solve the following non-linear optimization problem [16, Lemma 3]:

$$\underset{\boldsymbol{p}\ \in\ \mathcal{P}}{\text{maximize}} \quad \sum\nolimits_{r\in\mathcal{R}}\ f_\alpha\left(P_r^{\text{succ}}(\boldsymbol{p})\right) \tag{P1}$$

where

$$f_\alpha(P_r^{\text{succ}}) = -\alpha^{-1}(P_r^{\text{succ}})^{-\alpha}, \tag{12}$$

and $\alpha > 0$ is large (e.g., $\alpha \ge 10$). Function f_α in (12) is an *α-fair utility function* [16]. Solving the *network utility maximization* problem in (P1) is a common design objective in the networking literature (cf. [17], [18]). However, due to the multi-channel property of the RFID systems and the distinct features of the reader-to-reader and reader-to-tag interference models, problem (P1) is significantly different from the network utility maximization problems studied in [17], [18]. In particular, as we will see in Sections III and IV, solving problem (P1) is a challenging task due to the non-convexity of the interrogation success probability models in (9). For the rest of this paper, we focus on obtaining distributed algorithms to solve the max-min fair resource allocation problem in (P1).

III. Design I: Fully Distributed Algorithm

Although the utilities in (12) are concave functions in P_r^{succ} for $\alpha > 0$, problem (P1) is *not* a convex optimization problem with respect to $\boldsymbol{p}$, due to the *product forms* in (9). Thus, finding the optimal solution of problem (P1) is not easy in general. In this section, we discuss some properties of problem (P1) which allow us to develop our first distributed algorithm.

For each reader $r \in \mathcal{R}$, let $\boldsymbol{p}_r = (p_{r,c}\ \forall\ c \in \mathcal{C})$. In design I, the key idea is to use the *iterative coordinate ascent* method [19] to *locally* update the interrogation probabilities for each reader. In this method, we *fix* all of the components of vector $\boldsymbol{p}$ to some values, except for those components corresponding to *one* randomly selected reader (e.g., $\boldsymbol{p}_r$ for reader r). Then, in a *local* optimization procedure, we maximize the objective function of problem (P1) with respect to $\boldsymbol{p}_r$. This procedure is repeated, leading to an iterative algorithm. Iterative coordinate ascent algorithms are particularly useful when the original optimization problem is non-convex and difficult to solve, but each local optimization problem is convex and tractable.

A. Local Problem

Let $\boldsymbol{p}_{-r} = (p_{n,c}, \forall n \in \mathcal{R}\backslash\{r\}, c \in \mathcal{C})$. Consider the following *local* optimization problem in reader $r \in \mathcal{R}$:

$$\begin{aligned} \underset{\boldsymbol{p}_r \ge \boldsymbol{0}}{\text{maximize}} \quad & f_\alpha\left(P_r^{\text{succ}}\left(\boldsymbol{p}_r, \boldsymbol{p}_{-r}\right)\right) \\ & + \sum\nolimits_{n:r\in\mathcal{S}_n} f_\alpha\left(P_n^{\text{succ}}\left(\boldsymbol{p}_r, \boldsymbol{p}_{-r}\right)\right) \\ & + \sum\nolimits_{m:r\in\mathcal{I}_m} f_\alpha\left(P_m^{\text{succ}}\left(\boldsymbol{p}_r, \boldsymbol{p}_{-r}\right)\right) \\ & + \sum\nolimits_{k:r\notin\mathcal{S}_k\cup\mathcal{I}_k} f_\alpha\left(P_k^{\text{succ}}\left(\boldsymbol{p}_{-r}\right)\right) \\ \text{subject to} \quad & \left(\boldsymbol{p}_r, \boldsymbol{p}_{-r}\right) \in \mathcal{P}. \end{aligned} \tag{Local-P1}$$

[3] If $\Delta_{r,n}$ is known (by clock synchronization of readers), then $\gamma_{r,n} = 1$ if $-\tau_n(N_n) < \Delta_{r,n} < \tau_r(N_r)$; and $\gamma_{r,n} = 0$ otherwise.

Note that the objective functions in problems (Local-P1) and (P1) are the same. For the objective function in (Local-P1), the first term is *increasing* in $\boldsymbol{p}_r$. The second and third terms are *decreasing* in $\boldsymbol{p}_r$. The last term *does not depend* on $\boldsymbol{p}_r$ as for each reader k, such that $r \notin \mathcal{S}_k \cup \mathcal{I}_k$, probability P_k^{succ} does not depend on $\boldsymbol{p}_r$. By solving problem (Local-P1), reader r can select $\boldsymbol{p}_r$ such that the objective function in problem (P1) is maximized assuming that $\boldsymbol{p}_{-r}$ is fixed (i.e., none of the other readers change their interrogation probabilities). It is clear that reader r is assumed *not* to be selfish in this case. That is, it does not try to only maximize its own $f_\alpha(P_r^{\text{succ}})$. Instead, it *cooperates* with other readers. This is necessary for achieving the optimal RFID system performance in a *distributed* fashion. We can show the following key result.

Theorem 2: For each reader $r \in \mathcal{R}$, problem (Local-P1) is a *convex* optimization problem.

The proof of Theorem 2 is given in Appendix B. From Theorem 2, we can use various *convex programming* techniques to solve problem (Local-P1) in each reader $r \in \mathcal{R}$. In particular, problem (Local-P1) can be solved using the *interior-point method* (IPM) [20, Ch. 11] via *local* iterations if each reader can obtain the information on the interrogation probabilities of all readers within $d_{\max}^I = \max_{n \in \mathcal{R}} d_n^I$ distance away. Thus, the iterative coordinate ascent method is applicable.

Solving problem (Local-P1) requires *exchanging* some *control messages* among neighboring readers. We assume that all readers use a dedicated *control channel* with a frequency band different from those used for interrogation. The transmission power for the control messages is selected such that the *communication range* of the control channel becomes at least equal to $d_{\max}^I$. In that case, after updating $\boldsymbol{p}_r$, each reader $r \in \mathcal{R}$ can announce the new value of $\boldsymbol{p}_r$ to all readers within its $d_{\max}^I$ distance by *broadcasting* a control message. Let each probability value occupy M bytes (e.g., $M = 4$ for floating point numbers), then each control message has MC bytes, where C is the number of channels. Thus, solving problem (Local-P1) requires limited *local* signalling and is feasible, as opposed to solving the original non-convex problem (P1). This motivates us to propose our first algorithm.

B. FDFA Algorithm

Our proposed *fully distributed frequency allocation* (FDFA) algorithm for RFID systems is given in Algorithm 1. It is executed in each reader $r \in \mathcal{R}$. Let $\mathcal{T}_r^{\text{inter}}$ be an set of time instances at which reader r may start an interrogation interval based on probability vector $\boldsymbol{p}_r$. For any two consecutive elements $t_1, t_2 \in \mathcal{T}_r^{\text{inter}}$, we have $|t_2 - t_1| = T$. Let $\mathcal{T}_r^{\text{update}}$ be an unbounded set of time instances at which reader r updates its interrogation probability vector $\boldsymbol{p}_r$ by solving problem (Local-P1) using IPM. We assume that: (a) The updates are *asynchronous* across the readers in each neighborhood.[4] That is, for any $r, n \in \mathcal{R}$ such that $r \neq n$, we have: $\mathcal{T}_r^{\text{update}} \cap \mathcal{T}_n^{\text{update}} = \{\}$. (b) There is a global constant T^{update} such that for any $r \in \mathcal{R}$, there exists $t_1, t_2 \in \mathcal{T}_r^{\text{update}}$ such that $|t_1 - t_2| \leq T^{\text{update}}$. In other words, all readers update their interrogation probabilities at least once every T^{update} time units.

[4]This can be achieved if each reader broadcasts a *Busy* message on the control channel while it is updating its interrogation probability vector. No reader starts updating its interrogation probability vector if it is hearing a *Busy* message. This avoids any two neighboring readers update their interrogation probabilities *simultaneously*. Simultaneous updates may cause using some *outdated* information and result in a ping-pong effect, impeding convergence.

Algorithm 1 - FDFA: Executed by each reader $r \in \mathcal{R}$.

1: Allocate memory for $\boldsymbol{p}_r$ and $\boldsymbol{p}_{-r}$.
2: Randomly choose $\boldsymbol{p}_r$ and $\boldsymbol{p}_{-r}$ such that $(\boldsymbol{p}_r, \boldsymbol{p}_{-r}) \in \mathcal{P}$.
3: Set clock timer t.
4: **repeat**
5: **if** $t \in \mathcal{T}_r^{\text{update}}$ **then**
6: Solve problem (Local-P1) using IPM [20].
7: Update $\boldsymbol{p}_r$ according to the solution.
8: Broadcast a control message to announce $\boldsymbol{p}_r$.
9: **if** $t \in \mathcal{T}_r^{\text{inter}}$ **then**
10: Start an interrogation interval, using C1G2 MAC,
11: over frequency channel $c \in \mathcal{C}$, with probability $p_{r,c}$.
12: **if** a control message is received **then**
13: Update $\boldsymbol{p}_{-r}$ accordingly.
14: **until** reader device r stops operation.

In Algorithm 1, lines 5 to 14 are executed repeatedly until reader r stops operation. In lines 6 to 8, reader r updates $\boldsymbol{p}_r$ and broadcasts a control message including the updated entries of $\boldsymbol{p}_r$, whenever the current time is in set $\mathcal{T}_r^{\text{update}}$. In lines 10 and 11, reader r may start an interrogation according to its interrogation probability vector $\boldsymbol{p}_r$. Upon reception of a control message from another reader n, reader r updates its memory $\boldsymbol{p}_{-r}$ as in line 13. This implies that all elements of $\boldsymbol{p}_{-r}$ are updated in all readers $r \in \mathcal{R}$ within T^{update} time units.

C. Convergence, Optimality, and Complexity

In this section, we analytically investigate the convergence and optimality features of Algorithm 1. At each time instance $t \geq 0$, let $F_\alpha(t)$ denote the current value of the objective function for problem (P1). We can show the following.

Theorem 3: For any choice of system parameters and starting from any initial point:
(a) Function $F_\alpha(t)$ is *upper bounded*, i.e., $F_\alpha(t) \leq -\frac{R}{\alpha} \leq 0$.
(b) Function $F_\alpha(t)$ is *non-decreasing* in time $t \geq T^{\text{update}}$. That is, for any time instances $t_1, t_2 \geq T^{\text{update}}$ such that $t_1 \leq t_2$, we have $F_\alpha(t_1) \leq F_\alpha(t_2)$.
(c) Algorithm 1 converges to some F_α^*: $F_\alpha^* = \lim_{t \to \infty} F_\alpha(t)$.

The proof of Theorem 3 is given in Appendix C. Theorem 3 guarantees the convergence of Algorithm 1 for any choice of system parameters. We can further show that:

Theorem 4: Any *fixed point* of Algorithm 1 is a *stationary point* of problem (P1). That is, it is at least a *locally* optimal solution for the non-convex optimization problem (P1).

The proof of Theorem 4 is given in Appendix D. From Theorems 3 and 4, convergence and *local* optimality of Algorithm 1 are guaranteed. Clearly, the obtained interrogation probabilities may not necessarily be *globally* optimal. However, simulation results in Section V show that Algorithm 1 usually results in near globally optimal performance, making it a practical distributed frequency selection and randomized interrogation algorithm for large-scale RFID systems.

To understand the complexity of Algorithm 1, we notice that at each interrogation probability update interval (i.e., at each time $t \in \mathcal{T}_r^{\text{update}}$), we need to solve problem (Local-P1) using IPM. It is known that IPM has *polynomial* complexity [20]. Therefore, the complexity it takes to execute line 6 in Algorithm 1 is only a polynomial function of the *problem size*. Since problem (Local-P1) is a *local* problem for each reader $r \in \mathcal{R}$, the problem size is small. In fact, problem (Local-P1) has only C variables (e.g., $C = 10$ as in [10], [11]) and only a *single* linear constraint. Thus, Algorithm 1 is a tractable algorithm and can be used in practical RFID systems.

IV. Design II: Semi-Distributed Algorithm

For the FDFA algorithm in Section III, each reader can switch its channel whenever it starts an interrogation interval. Therefore, implementation of the FDFA algorithm requires RFID reader devices that are enabled to frequently switch their operating channel. However, in many of the existing reader technologies, the frequency switching delay is noticeable, e.g., in the order of several hundred milliseconds [21]. Therefore, as an alternative to the FDFA algorithm, in this section, we study the case where each reader operate on only one channel for a long period of time (e.g., several hours) and propose a semi-distributed algorithm which is guaranteed to reach the global optimum of the corresponding max-min fairness problem.

For each reader $r \in \mathcal{R}$ and any channel $c \in \mathcal{C}$, we define a new *discrete* variable $x_{r,c}$, with $x_{r,c} = 1$ if reader r operates on channel c, and $x_{r,c} = 0$ otherwise. Since each reader is assumed to operate on only one channel, we have

$$\sum\nolimits_{c\in\mathcal{C}} x_{r,c} = 1, \qquad \forall r \in \mathcal{R}. \tag{13}$$

Clearly, if reader $r \in \mathcal{R}$ does *not* operate on a channel $c \in \mathcal{C}$ (i.e., $x_{r,c} = 0$), then the interrogation probability of reader r on channel c (i.e., $p_{r,c}$) is zero. This requires that

$$p_{r,c} \le x_{r,c}, \qquad \forall r \in \mathcal{R},\ c \in \mathcal{C}. \tag{14}$$

From (13) and (14), the *max-min* fair problem, when each reader uses only one channel, becomes

$$\underset{\boldsymbol{p}\in\mathcal{P}(\boldsymbol{x}),\ \boldsymbol{x}\in\mathcal{X}}{\text{maximize}} \quad \sum\nolimits_{r\in\mathcal{R}} f_\alpha\left(P_r^{\text{succ}}(\boldsymbol{p})\right) \tag{P2}$$

where

$$\boldsymbol{x} = (x_{r,c},\ \forall r \in \mathcal{R}, c \in \mathcal{C}), \tag{15}$$

and

$$\mathcal{X} = \left\{\, \boldsymbol{x} : \sum\nolimits_{c\in\mathcal{C}} x_{r,c} = 1,\ x_{r,c} \in \{0,1\}, \forall\, r \in \mathcal{R}, c \in \mathcal{C} \,\right\}, \tag{16}$$

and for each $\boldsymbol{x} \in \mathcal{X}$, we have

$$\mathcal{P}(\boldsymbol{x}) = \left\{\, \boldsymbol{p} : p_{r,c} \le x_{r,c},\ p_{r,c} \in [0,1], \forall\, r \in \mathcal{R}, c \in \mathcal{C} \,\right\}. \tag{17}$$

Problem (P2) is a *non-linear mixed-integer* optimization problem, which is difficult to solve in general. To solve problem (P2), we need to deal with the non-convexity with respect to $\boldsymbol{p}$ due the product forms in (9). Also note that problem (P2) has both *continuous* and *discrete* variables.

To solve problem (P2), we use the *generalized Benders decomposition* [22, pp. 114-143] and decompose problem (P2) into two sub-problems: (a) a *primal* problem which is a tractable *continuous* optimization problem with respect to interrogation probabilities $\boldsymbol{p}$; and (b) a *master* problem which is a *discrete* optimization problem with respect to channel allocation variables $\boldsymbol{x}$. The solution of the primal problem provides a *lower bound* on the optimal value of the original problem (P2), while the solution of the master problem provides an *upper bound*. Under certain conditions, the iteratively obtained lower and upper bounds converge to each other in finite time, leading to the global optimal solution of the non-linear mixed-integer optimization problem (P2).

A. Primal and Master Problems

Given any channel assignment vector $\boldsymbol{x} \in \mathcal{X}$, we define the *primal* problem to be as follows:

$$\underset{\boldsymbol{p}\in\mathcal{P}(\boldsymbol{x})}{\text{maximize}} \ \sum\nolimits_{r\in\mathcal{R}} f_\alpha\left(P_r^{\text{succ}}(\boldsymbol{p})\right). \tag{Primal-P2}$$

The objective functions in problems (Primal-P2) and (P1) are the same. Moreover, probabilities $\boldsymbol{p}$ in (Primal-P2) should satisfy (14) for given $\boldsymbol{x}$. With (13), this implies that each reader has *non-zero* interrogation probability on *one* channel.

Lemma 1: For any $\boldsymbol{x} \in \mathcal{X}$, problem (Primal-P2) can be transformed into an *equivalent convex* problem with *zero* duality gap and *unique* stationary point by change of variables.

The proof of Lemma 1 is given in Appendix E. From Lemma 1, problem (Primal-P2) is indeed a tractable optimization problem. To show this, for each reader $r \in \mathcal{R}$, we define $\boldsymbol{x}_r = (x_{r,c},\ \forall c \in \mathcal{C})$. Consider the following *local* and *myopic* optimization problem in reader $r \in \mathcal{R}$:

$$\underset{\boldsymbol{p}_r\in\mathcal{P}_r(\boldsymbol{x}_r)}{\text{maximize}} \ \sum\nolimits_{n\in\mathcal{R}} f_\alpha\left(P_n^{\text{succ}}(\boldsymbol{p}_r, \boldsymbol{p}_{-r})\right), \tag{Local-Primal-P2}$$

where $\mathcal{P}_r(\boldsymbol{x}_r) = \left\{\, \boldsymbol{p}_r : p_{r,c} \le x_{r,c},\ p_{r,c} \in [0,1], \forall\, c \in \mathcal{C} \,\right\}$. From Lemma 1 and Theorem 4, given $\boldsymbol{x} \in \mathcal{X}$, the iterative coordinate ascent method can be used to obtain the *unique* local (thus *global*) optimal solution of problem (Primal-P2). That is, given the operating channels $\boldsymbol{x}$ for all readers, we can distributively find the corresponding exact global optimal interrogation probabilities by repeatedly solving problem (Local-Primal-P2) among all readers. Thus, an algorithm *similar* to Algorithm 1 is sufficient to solve problem (Primal-P2).

Using the generalized Benders decomposition, we also iteratively solve an optimization problem, called *master* problem, to obtain channel allocation vector $\boldsymbol{x}$. Let $\boldsymbol{x}^{*(k)}$ denote the solution of the master problem at the k^{th} iteration, where $\boldsymbol{x}^{*(1)}$ is selected *randomly*. Given $\boldsymbol{x}^{*(k)} \in \mathcal{X}$, let $\boldsymbol{p}^{*(k)}$ denote the solution of problem (Primal-P2) at $\boldsymbol{x}^{*(k)}$. Let $\boldsymbol{\lambda}^{*(k)} = (\lambda_{r,c}^{*(k)},\ \forall\, r \in \mathcal{R},\ c \in \mathcal{C})$ denote the vector of *Lagrange multipliers* for the constraints in (14) at solution $\boldsymbol{p}^{*(k)}$. From [22, Ch. 6.5] we construct the *master* problem at iteration $k{+}1$:

$$\begin{aligned} &\underset{\boldsymbol{x}\in\mathcal{X},\ \mu\ge 0}{\text{maximize}} \quad \mu \\ &\text{subject to} \quad \mu \le \sum\nolimits_{r\in\mathcal{R}} \sum\nolimits_{c\in\mathcal{C}} \lambda_{r,c}^{*(j)} x_{r,c} + L_\alpha^{*(j)},\ \forall\, j = 1, \ldots, k, \end{aligned} \tag{Master-P2}$$

where the term $\sum_{r\in\mathcal{R}} \sum_{c\in\mathcal{C}} \lambda_{r,c}^{*(j)} x_{r,c} + L_\alpha^{*(j)}$ denotes the *dual function* of problem (Primal-P2), given $\boldsymbol{x}^{*(j)}$, at $\boldsymbol{p}^{*(j)}$ and

$\boldsymbol{\lambda}^{*(j)}$, when $\boldsymbol{x}^{*(j)}$ is replaced by $\boldsymbol{x}$. Here, we have

$$L_\alpha^{*(j)} = F_\alpha^{*(j)} - \sum_{r\in\mathcal{R}} \sum_{c\in\mathcal{C}} \lambda_{r,c}^{*(j)}\, p_{r,c}^{*(j)}, \qquad j = 1, \ldots, k, \tag{18}$$

where $F_\alpha^{*(j)} = \sum_{r\in\mathcal{R}} f_\alpha(P_r^{\text{succ}}(\boldsymbol{p}^{*(j)}))$ denotes the objective function of problem (Primal-P2) at optimal point $\boldsymbol{p}^{*(j)}$. Notice that $L_\alpha^{*(j)}$ does *not* depend on $\boldsymbol{x}$. Problem (Master-P2) is a *linear* binary optimization problem. It can be solved by using the CPLEX [23] or MOSEK [24] optimization software.

Let $\boldsymbol{x}^{*(k+1)}$ and $\mu^{*(k+1)}$ denote the optimal solutions of problem (Master-P2) at iteration $k+1$. By *weak duality* [20, p. 225], $\mu^{*(k+1)}$ is an *upper-bound* for the optimum of problem (P2). $F_\alpha^{*(k)}$ is a *lower-bound* for the optimum of problem (P2) as it corresponds to the maximum of problem (P2) for one choice of channel allocation $\boldsymbol{x}$. Since problem (Master-P2) has *more constraints* at iteration $k+1$ than at iteration k for any $k \geq 1$, we have $\mu^{*(k+1)} \leq \mu^{*(k)}$. That is, the *upper-bound sequence* $\{\mu^{*(k)}\}$ is *non-increasing*. On the other hand, the *lower-bound sequence* $\{\max_{j=1,\ldots,k} F_\alpha^{*(j)}\}$ is *non-decreasing* by construction. Since the primal problem has *zero duality gap*, from [22, Theorem 6.3.4], we obtain the following theorem.

Theorem 5: Starting from any $\boldsymbol{x} \in \mathcal{X}$ and $\boldsymbol{p} \in \mathcal{P}(\boldsymbol{x})$, the global optimal solution of the non-linear mixed-integer problem (P2) can be found in *finite* time by iteratively solving problems (Primal-P2) and (Master-P2). The upper and lower bound sequences converge to each other.

B. SDFA Algorithm

Our *semi-distributed frequency allocation* (SDFA) algorithm for RFID systems is given jointly by Algorithms 2 and 3. Algorithm 2 is executed by each reader r and Algorithm 3 is executed by the back-end system. The sets $\mathcal{T}_r^{\text{inter}}$ and $\mathcal{T}_r^{\text{update}}$ for each reader r are the same as those in Section III-B. In Algorithm 3, $\mathcal{T}^{\text{channel}}$ denotes an unbounded set of time instances at which the back-end system updates the channel allocation vector $\boldsymbol{x}$ by solving problem (Master-P2). In line 3, we set the upper and lower bound variables UBD and LBD to be ∞ and $-\infty$, respectively. They are reset in line 18 whenever the RFID system has a change of topology (due to relocation of readers). Lines 7 to 16 are executed periodically. In line 10, we update LBD to be equal to the *best* optimal value for problem (Primal-P2) so far. Lines 12 to 16 are executed if the lower and upper bounds are *not* close enough yet. The convergence of Algorithm 2 follows from Lemma 1 and Theorems 3(c) and 4. The convergence of Algorithm 3 follows from Theorem 5.

The complexity of Algorithm 2 is the same as that of Algorithm 1. Problem (Local-Primal-P2) can be solved in polynomial time. However, Algorithm 3 has non-polynomial complexity as it requires solving an integer problem in line 13. Nevertheless, since Algorithm 3 needs to be executed in the back-end system (not at readers), various efficient commercial optimization software such as CPLEX [23] or MOSEK [24] can be used to solve problem (Master-P2) in reasonable time. Finally, we notice that in case of full coordination among the readers and the back-end system, the SDFA algorithm can also be implemented at the back-end system in a centralized fashion to tackle the non-convexity of problem (P2).

Algorithm 2 - SDFA: Executed by each reader $r \in \mathcal{R}$.

1: Allocate memory for $\boldsymbol{p}_r$ and $\boldsymbol{p}_{-r}$, $\boldsymbol{x}$, and $\boldsymbol{\lambda}_r$.
2: Set $x_{n,1} = 1$ and $x_{n,c} = 0$ for all $n \in \mathcal{R}$ and any $c \in \mathcal{C}\backslash\{1\}$.
3: Randomly choose $\boldsymbol{p}_r$ and $\boldsymbol{p}_{-r}$ such that $(\boldsymbol{p}_r, \boldsymbol{p}_{-r}) \in \mathcal{P}(\boldsymbol{x})$.
4: Set clock timer t.
5: **repeat**
6: **if** $t \in \mathcal{T}_r^{\text{update}}$ **then**
7: Solve problem (Local-Primal-P2) using IPM [20].
8: Update $\boldsymbol{p}_r$ and $\boldsymbol{\lambda}_r$ according to the solution.
9: Broadcast a control message to announce $\boldsymbol{p}_r$.
10: **if** $t \in \mathcal{T}_r^{\text{inter}}$ **then**
11: Start an interrogation interval, using C1G2 MAC,
12: over frequency channel $c \in \mathcal{C}$, with probability $p_{r,c}$.
13: **if** a control message is received **then**
14: Update $\boldsymbol{p}_{-r}$ accordingly.
15: **if** back-end system asked for information **then**
16: Convey $\boldsymbol{p}_r$ and $\boldsymbol{\lambda}_r$ to the back-end system.
17: Update $\boldsymbol{x}$ according to the new channel assignment.
18: Randomly set $\boldsymbol{p}_r$ and $\boldsymbol{p}_{-r}$ such that $(\boldsymbol{p}_r, \boldsymbol{p}_{-r}) \in \mathcal{P}(\boldsymbol{x})$.
19: **until** reader r stops operation.

Algorithm 3 - SDFA: Executed by the back-end system.

1: Allocate memory for LBD, UBD and sequences $\{\boldsymbol{p}^{*(k)}\}$, $\{\boldsymbol{\lambda}^{*(k)}\}$, $\{\boldsymbol{x}^{*(k)}\}$, $\{\mu^{*(k)}\}$, $\{F_\alpha^{*(k)}\}$, and $\{L_\alpha^{*(k)}\}$.
2: For all $r \in \mathcal{R}$, set $x_{r,1} = 1$ and $x_{r,c} = 0$ for any $c \in \mathcal{C}\backslash\{1\}$.
3: Set $UBD = \infty$, $LBD = -\infty$, $k = 1$, and $\epsilon = 10^{-6}$.
4: Set clock timer t.
5: **repeat**
6: **if** $t \in \mathcal{T}^{\text{channel}}$,
7: Collect $\boldsymbol{p}_r^{*(k)}$ and $\boldsymbol{\lambda}_r^{*(k)}$ from all readers $r \in \mathcal{R}$.
8: Set $F_\alpha^{*(k)} = \sum_{r\in\mathcal{R}} f_\alpha(P_r^{\text{succ}}(\boldsymbol{p}_r^{*(k)}))$.
9: Set $L_\alpha^{*(k)} = F_\alpha^{*(k)} - \sum_{r\in\mathcal{R}} \sum_{c\in\mathcal{C}} \lambda_{r,c}^{*(k)}\, p_{r,c}^{*(k)}$.
10: Set $LBD = \max\{LBD, F_\alpha^{*(k)}\}$.
11: **if** $UBD - LBD \geq \epsilon$ **then**
12: Set $k = k + 1$.
13: Solve problem (Master-P2) using MOSEK [24].
14: Update $\boldsymbol{x}^{*(k)}$ and $\mu^{*(k)}$ according to the solution.
15: Set $UBD = \mu^{*(k)}$.
16: Convey $\boldsymbol{x}^{*(k)}$ to all readers.
17: **if** topology has changed **then**
18: Set $UBD = \infty$, $LBD = -\infty$, and $k = 1$.
19: **until** RFID system stops operation.

V. Performance Evaluation

In this section, we evaluate the performance of the proposed FDFA and SDFA algorithms and compare them with five other distributed randomized interrogation schemes: DIA [10], S-LBT [11], FH-LBT [12], as well as random and naive algorithms [9]. We also assess the convergence, optimality, and robustness properties of the FDFA and SDFA algorithms. We assume that 40 readers are randomly deployed in a $50 \times 50m^2$ warehouse such that complete interrogation coverage is achieved. Some spots can be within the read areas of multiple readers. For each reader r, the interrogation range d_r^R is 5 m. The interference range d_r^I is 8.5 m [21]. On average, there are 1,000 uniformly distributed tags located within the interrogation range of each reader. The interrogation interval is $T = 10$ sec. We set $\alpha = 10$ [25]. The average time to finish a successful interrogation is 2.5 sec, assuming that the enhanced dynamic framed slotted Aloha [15] is used. We set $\tau^{\text{slot}} = 1\ ms$. Problems (Local-P1), (Local-Primal-P2), and

(Master-P2) are solved by using the MOSEK software [24].

Although we used the protocol model [26, Section I-A.1] in our design phases in Sections IV and III, here in the simulations we use the physical model [26, Section I-A.2]. Different from the protocol model which incorporates only the *pairwise interference*, e.g., from one reader to another reader, the physical model is based on the *signal-to-interference-plus-noise-ratio* (SINR) and incorporates the impact of *aggregate interference* from multiple interference sources. The protocol model is more tractable and useful for our design phase. However, by using the physical model in our simulations, we can better assess our algorithms in more realistic settings.

The simulation parameters are as follows. For each tag, the transmit power is 10 mW [27]. The transmit power for each reader is 40 mW. Note that since the readers are more sophisticated devices, they can transmit at higher power levels than the tags [27]. A deterministic path loss, based on the Friis free space model, with an exponent equal to three [28], is considered in order to calculate the received signal power and the aggregate interference power at each reader and each tag. Without loss of generality, we assume that the noise level is -80 dBm. We define three interference thresholds, denoted by $\mathcal{I}_{RR}$, $\mathcal{I}_{RT1}$, and $\mathcal{I}_{RT2}$, corresponding to the three different collision scenarios defined in Section II. In our model, for each reader, reader-to-reader collision occurs when the aggregate interference power from all readers plus the noise power exceeds the interference threshold $\mathcal{I}_{RR} = -27$ dBm. That is, the reader-to-reader collision occurs if and only if the SINR drops below the typical operation level at 2 dB. We also note that if there are only two readers, then the interference exceeds $\mathcal{I}_{RR} = -27$ dBm if and only if the two readers are located within $d_r^I = 8.5\ m$, i.e., the interference range already defined for the protocol model. Similarly, we set $\mathcal{I}_{RT1} = -27$ dBm. This threshold indicates the maximum aggregate reader-to-tag interference over the same channel which allows each tag to correctly detect the interrogation signal from its corresponding reader. Finally, we set $\mathcal{I}_{RT1} = -10$ dBm. The rational behind this choice is as follows. Recall that the Type 2 reader-to-tag collision occurs if *at least* one tag among all the tags inside the read range of one reader is also located inside the read range of another reader. Given a read range of 5 m, the interference level exceeds -10 dBm when a tag is within the interrogation range of more than one reader. By taking into account all three collision models, an interrogation attempt by a reader is successful if and only if the SINR at *every* tag within the reader's read range is above the three threshold levels.

A. Comparison with Other Distributed Algorithms

We compare the FDFA and SDFA algorithms with DIA [10], S-LBT [11], FH-LBT [12], and random and naive algorithms [9] in terms of the average probability of a successful interrogation among *all* readers (i.e., the ratio of the successfully interrogated tags compared to the total number of tags in the system). For the DIA algorithm, following the choices of parameters in [10], we set $T_{sleep\_init} = 10$, $T_{to\_init} = 20$ ms, $T_{md\_max} = 10$ ms, and $T_{check} = 10$ ms. For both S-LBT and FH-LBT algorithms, the carrier sensing time is set to 10 ms. For the random algorithm, the back-off time is randomly selected within the range of 5 sec and 15 sec as in [11]. Finally, for the naive algorithm, the time interval between any two subsequent interrogations is 10 sec. The simulation time is 1,000 sec. The results when the number of channels C varies from 1 to 15 are shown in Fig. 5. In this figure, each point represents the *average* results of simulating 100 different randomly generated topologies. We can see that, for all algorithms, the probabilities increase as more channels become available. However, FDFA and SDFA algorithms always outperform the other heuristic algorithms. Notice that all algorithms reach some *saturation* levels, which are *not* the same for all algorithms. Recall from Section II that reader-to-reader and type 1 reader-to-tag collisions can be avoided if the neighboring readers operate on different channels. However, having the readers operate on different channels *cannot* avoid *type 2* reader-to-tag collision. Thus, if the number of channels is high, different algorithms differ depending on their type 2 reader-to-tag collision avoidance. From Fig. 5, the FDFA algorithm can better avoid type 2 reader-to-tag collisions than the other algorithms. Similar results are obtained for the SDFA algorithm as it also outperforms all other heuristic algorithms. However, we can see that although the SDFA algorithm results in finding the global optimum of problem (P2), it leads to a worse performance compared to the FDFA algorithm, which only finds a local optimum of problem (P1). As we will explain in Section V-B, this is because problem (P2) is more restrictive (i.e., has a smaller feasible set) compared to problem (P1).

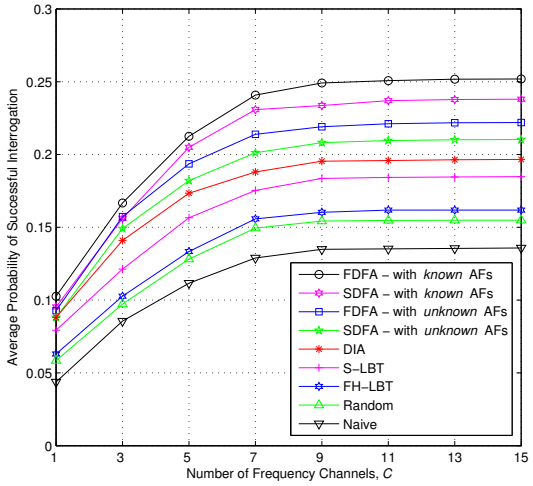


Fig. 5. Comparison between the proposed FDFA and SDFA algorithms and DIA [10], S-LBT [11], FH-LBT [12], and random and naive [9] algorithms when the number of available frequency channels varies from 1 to 15.

Next, we investigate *fairness* (i.e., *balanced* performance) among readers. Following the same simulation model as in [10], [11], we assume that the number of channels is $C = 10$. The simulation time is 1,000 sec. We compare the *minimum* number of successful interrogations among readers for different algorithms. Results are shown in Fig. 6. Each curve represents the *average* results of simulating 100 topologies. We can see that FDFA and SDFA algorithms perform better than all the heuristic algorithms as *max-min* fairness is indeed the *design objective* for both FDFA and SDFA. Using FDFA,

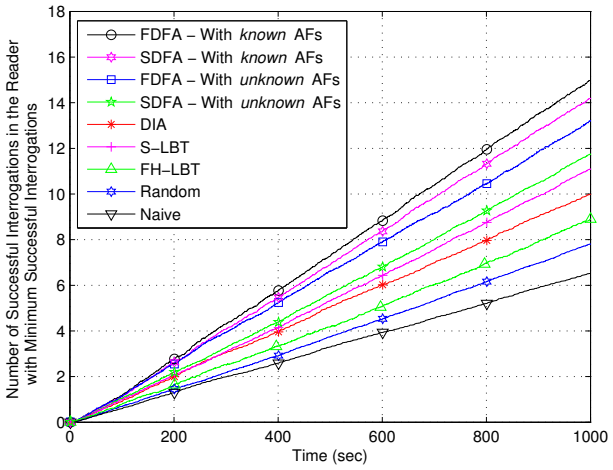


Fig. 6. Comparison between the proposed FDFA and SDFA algorithms with the DIA [10], S-LBT [11], FH-LBT [12], and also random and naive [9] algorithms in terms of max-min fairness.

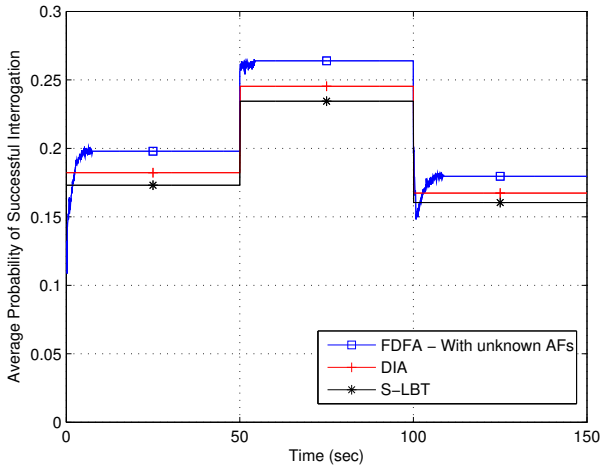


Fig. 7. Convergence and robustness properties of the FDFA algorithm and comparison with the DIA [10] and S-LBT [11] algorithms. The location of five readers change at times $t=50$ sec and $t=100$ sec, respectively.

if *asynchronism factors* (AFs) (i.e., $\Delta_{r,n}$ for all $r, n \in \mathcal{R}$) are *unknown*, the *minimum* number of successful interrogations among all readers, which is measured at the end of the simulation is 20. We notice that as each interrogation interval is $T = 10$ sec, there are in total $\frac{1000}{10} = 100$ interrogation attempts during the simulation time. Since, at worst case, 20 out of 100 attempts are successful when the FDFA algorithm is used, the minimum probability of successful interrogation among all readers is almost 0.132. This is, 19%, 32%, 48%, 69%, and 101% higher than for DIA, S-LBT, FH-LBT, random, and naive algorithms, respectively. If the AFs are *known*, then the minimum probability of successful interrogation further increases by 12%. Notice that by achieving max-min fairness, the processing load becomes similar for all readers. Furthermore, the interrogation performance becomes balanced among different spots of the covered warehouse.

B. Convergence, Robustness, and Optimality Properties

Recall that the convergence of the FDFA algorithm to a local optimum of problem (P1) is guaranteed by Theorems 3(c) and 4. Consider an RFID system with 10 readers. The simulation time is divided into *three phases* and each phase is 50 sec. The first phase starts at time $t=0$, where all readers start operation. At time $t=50$ sec, five readers move to some *new locations* such that they experience *less* interference. That is, they move *away* from each other. Later on, at time $t=100$ sec, those five readers move back *towards* each other; however, they do not become as close as their initial locations. Results are shown in Fig. 7. Here, $T_r^{\text{update}} = 1$ sec. We see that FDFA enjoys fast convergence in all phases[5]. Note that, due to topology changes, the system parameters also change, leading to distinct optimal solutions for problem (P1) in each phase. The fast convergence speed for the FDFA algorithm is mainly due to the use of the *coordinate ascent method*. Similar results on the fast convergence of the wireless networking algorithms which use the *coordinate ascent method* have been reported in [18].

Recall from Theorem 5 that the upper and lower bounds in the SDFA algorithm are guaranteed to converge to each other, leading to the *global* optimal solution of problem (P2). Fig. 8 shows the upper and lower bound sequences for a randomly generated RFID topology with 25 readers and 10 channels. We can see that the upper and lower bounds converge after only 21 iterations. From the results in Fig. 8, the optimal value of problem (P2) is -2893. It is interesting to compare this value with the *global* optimum of problem (P1), which is -2595 (i.e., 10.3% higher). Notice that problem (P2) restricts each reader to operate only on one channel. Thus, it has *more constraints* than problem (P1). Therefore, the optimal value of problem (P1) is always greater than or equal to the optimal value of problem (P2). Also notice that since the SDFA algorithm converges fast, e.g., after only 21 iterations in this case, the number of constraints in problem (Master-P2), which are added after each iteration, is limited, e.g., up to 21 constraints. Therefore, problem (Master-P2) is tractable and the SDFA algorithm has a low complexity.

Next, we investigate optimality. Recall that both FDFA and SDFA algorithms aim to maximize the objective value of the max-min fairness problem (i.e., $\sum_{r\in\mathcal{R}} f_\alpha(P_r^{\text{succ}}(\boldsymbol{p}))$), subject to *different* constraints. In particular, FDFA and SDFA are designed to find the local and global optimal solutions for problems (P1) and (P2), respectively. We determine the percentage difference of the optimal values obtained from FDFA and SDFA algorithms to the *global* optimal value of problem (P1). We consider 100 randomly generated topologies, each has 40 readers and 10 channels. The global optimum of problem (P1) is *approximately* obtained by running the FDFA algorithm 100 times, with each time starting from a *different* randomly selected *initial point*. The global optimal value is then selected to be the *maximum* observed local optimal value among all 100 simulations. Results are shown in Fig. 9. On average, the FDFA algorithm achieves 93.2% of

[5]In Fig. 7, although we can compare FDFA with the DIA and S-LBT in terms of interrogation success probability at each phase, we cannot compare them in terms of convergence speed. Since the DIA and the S-LBT algorithms are *not* iterative, the concept of convergence does not apply to them.

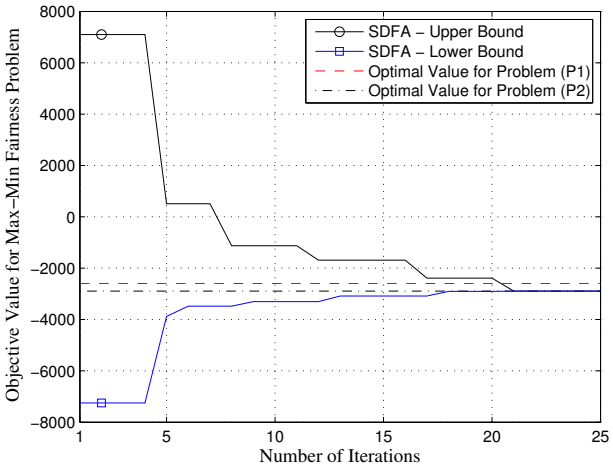


Fig. 8. Convergence of the lower and upper bounds in the SDFA algorithm. We can see that the global optimal solution of problem (P2) can be found after 21 iterations when the lower and upper bounds reach the same value.

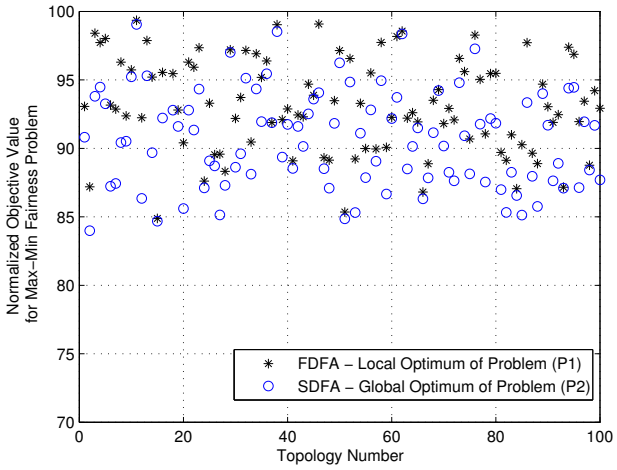


Fig. 9. Comparison between the FDFA and SDFA algorithms in terms of maximizing the objective value for max-min fairness problems (P1) and (P2).

the global optimal value of problem (P1). This implies *near* optimal performance for FDFA. On the other hand, the global optimal value of problem (P2), obtained by using SDFA, is 90.8% of the global optimal value for problem (P1). This implies that restricting each reader to operate on one channel for a long time, results in 9.3% lower objective values. In summary, we conclude that if the switching delay is small enough such that each reader can switch to a new channel in each interrogation interval, then FDFA can be used as it has *near* optimal performance in terms of solving problem (P1). However, if each reader only operates on one channel for several intervals, then SDFA can be used to solve (P2).

VI. Conclusion

In this paper, we systematically studied the frequency channel selection and randomized interrogation problems for large-scale and dense RFID systems. We first modeled the reader-to-reader collision and reader-to-tag collisions (both types) in RFID systems. We then derived the probability of performing a successful interrogation for each reader, where the readers operate asynchronously. The joint channel selection and randomized interrogation problem was formulated as a *max-min* fair resource allocation problem. We proposed two distributed algorithms to solve the optimization problem. The first algorithm, called FDFA, is *fully distributed* and is guaranteed to achieve a local optimum. It works based on the *iterative coordinate ascent* update mechanism. It allows each reader to frequently switch its operating channel. The second algorithm, called SDFA, is *semi-distributed* and is guaranteed to achieve the *global* optimum. The SDFA algorithm uses the *generalized Benders decomposition* and restricts each reader to operate on one channel for a long time. Simulation results show that both FDFA and SDFA have better performance than the previously proposed heuristic channel selection and reader anti-collision algorithms in terms of the number of correct interrogations and fairness among readers. They also better utilize the frequency spectrum and have fast convergence speed.

Appendix

A. Proof of Theorem 1

We first prove (10). Given (8), for each pair $r, n \in \mathcal{R}$, an interrogation cycle (which consists of all interrogation frames within an interrogation interval) for reader n (with duration $\tau_n(N_n)$) may overlap with only *one* interrogation cycle of reader r (with duration $\tau_r(N_r)$). To obtain the probability of overlap, we only need to consider the period $-T/2 \leq \Delta_{r,n} \leq T/2$. From Fig. 4, we can see that overlapping of interrogation cycles between readers r and n occurs when

$$-\tau_n(N_n) < \Delta_{r,n} < \tau_r(N_r). \tag{19}$$

Since readers *randomly* and *independently* start up their operation, $\Delta_{r,n}$ has a uniform distribution over $-T/2$ and $T/2$. Thus, the probability of (19) happening is as in (10). Next, we notice that for each reader $r \in \mathcal{R}$, the probability of completing a successful interrogation is obtained as

$$P_r^{\text{succ}}(\boldsymbol{p}) = \textstyle\sum_{c\in\mathcal{C}} \; p_{r,c} \; \mathbb{P}\left(A_{r,c}^{\text{NoRR}} \cap A_{r,c}^{\text{NoRT1}} \cap A_{r,c}^{\text{NoRT2}}\right), \tag{20}$$

where $\mathbb{P}(A_{r,c}^{\text{NoRR}} \cap A_{r,c}^{\text{NoRT1}} \cap A_{r,c}^{\text{NoRT2}})$ denotes the probability that *no* reader collision occurs while reader r is performing an interrogation on channel c. $A_{r,c}^{\text{NoRR}}$, $A_{r,c}^{\text{NoRT1}}$, and $A_{r,c}^{\text{NoRT2}}$ correspond to the events where *no* reader-to-reader collisions, *no* type 1 reader-to-tag collisions, and *no* type 2 reader-to-tag collisions occur, respectively. Since $\mathcal{V}_r \subseteq \mathcal{I}_r \cup \mathcal{S}_r$, if reader-to-tag collisions do not happen, then reader-to-reader collision cannot happen either. Thus, we have

$$\mathbb{P}(A_{r,c}^{\text{NoRR}} \cap A_{r,c}^{\text{NoRT1}} \cap A_{r,c}^{\text{NoRT2}}) = \mathbb{P}(A_{r,c}^{\text{NoRT1}} \cap A_{r,c}^{\text{NoRT2}}). \tag{21}$$

Moreover, since $A_{r,c}^{\text{NoRT1}}$ and $A_{r,c}^{\text{NoRT2}}$ are independent events due to (3), $\mathbb{P}(A_{r,c}^{\text{NoRT1}} \cap A_{r,c}^{\text{NoRT2}}) = \mathbb{P}(A_{r,c}^{\text{NoRT1}})\ \mathbb{P}(A_{r,c}^{\text{NoRT2}})$. Finally, we can show that for all $c \in \mathcal{C}$, we have

$$\mathbb{P}(A_{r,c}^{\text{NoRT1}}) = \textstyle\prod_{n\in\mathcal{I}_r} (1 - \gamma_{r,n}\, p_{n,c}) \tag{22}$$

and

$$\mathbb{P}(A_{r,c}^{\text{NoRT2}}) = \textstyle\prod_{n\in\mathcal{S}_r} \left(1 - \gamma_{r,n} \sum_{e\in\mathcal{C}} p_{n,e}\right), \tag{23}$$

where $\sum_{e\in\mathcal{C}} p_{n,e}$ denotes the probability that reader n starts an interrogation interval over *any* of the available channels. Replacing (21), (22), and (23) in (20), we obtain (9). ■

B. Proof of Theorem 2

By replacing (9) into the objective in (Local-P1), it becomes

$$f_\alpha\left(\sum_{c\in\mathcal{C}}\theta_{r,c}\,p_{r,c}\right)+\sum_{n:r\in\mathcal{S}_n} f_\alpha\left(\vartheta_{r,n}(1-\gamma_{r,n}\sum_{c\in\mathcal{C}}p_{r,c})\right) + \sum_{m:r\in\mathcal{I}_m} f_\alpha\left(\sum_{c\in\mathcal{C}}\zeta_{r,m,c}(1-\gamma_{r,m}p_{r,c})\right)+\xi_r, \tag{24}$$

where

$$\theta_{r,c}=\left(\prod_{i\in\mathcal{S}_r}(1-\gamma_{r,i}\sum_{e\in\mathcal{C}}p_{i,e})\right)\left(\prod_{j\in\mathcal{I}_r}(1-\gamma_{r,j}p_{j,c})\right), \tag{25}$$

$$\vartheta_{r,n}=\left(\prod_{i\in\,\mathcal{S}_n\setminus\{r\}}(1-\gamma_{i,n}\sum_{e\in\mathcal{C}}p_{i,e})\right)\left(\sum_{e\in\mathcal{C}}p_{n,e}\left(\prod_{j\in\mathcal{I}_n}(1-\gamma_{n,j}\,p_{j,e})\right)\right), \tag{26}$$

$$\zeta_{r,m,c}=p_{m,c}\left(\prod_{i\in\mathcal{I}_m\setminus\{r\}}(1-\gamma_{m,i}\,p_{i,c})\right)\left(\prod_{j\in\mathcal{S}_m}(1-\gamma_{m,j}\sum_{e\in\mathcal{C}}p_{j,e})\right), \tag{27}$$

and

$$\xi_r=\sum_{k\,:\,r\notin\mathcal{S}_k\cup\mathcal{I}_k} f_\alpha(P_k^{\text{succ}}(\boldsymbol{p}_{-r})). \tag{28}$$

Note that $\theta_{r,c}$, $\vartheta_{r,n}$, $\zeta_{r,m,c}$, and ξ_r only depend on $\boldsymbol{p}_{-r}$. They can be treated as constants in problem (Local-P1). Since f_α is concave for $r\in\mathcal{R}$, the objective function of problem (Local-P1) is a *concave-affine* composition over $\boldsymbol{p}_r$. Thus, it is concave [20, p. 84]. Since the constraint in (Local-P1) is *linear*, problem (Local-P1) is a convex problem. ■

C. Proof of Theorem 3

Part (a): Since $P_r^{\text{succ}}\le 1$, $f_\alpha(P_r^{\text{succ}})\le f_\alpha(1)=-1/\alpha$.

Part (b): We prove this part by contradiction. First, we assume that $F_\alpha(t_1)>F_\alpha(t_2)$. In that case, there exists a time instance $t\in[t_1,t_2]$ such that running Algorithm 1 results in *reducing* the value of the objective function of problem (P1) at time t. In other words, there exists a reader $r\in\mathcal{R}$ such that $t\in\mathcal{T}_r^{\text{update}}$ and F_α is reduced by executing line 6 of Algorithm 1 in reader r. However, this is impossible as the objective function in problem (P1) is the same as that in problem (Local-P1). Thus, we indeed have $F_\alpha(t_1)\le F_\alpha(t_2)$.

Part (c): The limit in this part directly results from Parts (a) and (b). Notice that any upper bounded non-decreasing sequence of real numbers converges to a fixed point. ■

D. Proof of Theorem 4

Let $\boldsymbol{p}^*$ denote any fixed point of Algorithm 1. Given $\boldsymbol{p}_{-r}=\boldsymbol{p}^*_{-r}$ for $r\in\mathcal{R}$, $\boldsymbol{p}_r=\boldsymbol{p}^*_r$ is optimum for problem (Local-P1). Since (Local-P1) is *convex*, $\boldsymbol{p}^*$ should satisfy the Karush-Kuhn-Tucker (KKT) conditions [20, p. 244] corresponding to (Local-P1) for all $r\in\mathcal{R}$. By definition, each stationary point [29, p. 194] of *non-convex* problem (P1) also satisfies all the KKT conditions for problem (P1). Since the objective functions in (P1) and (Local-P1) are the same and the set of constraints in (P1) is the *union* of those in (Local-P1) for all $r\in\mathcal{R}$, the KKT conditions for (P1) are equal to the *union* of the KKT conditions for (Local-P1) for all $r\in\mathcal{R}$. Thus, since $\boldsymbol{p}^*$ satisfies the KKT conditions of Local-P1) for *all* readers, it also satisfies the KKT conditions for P1), i.e., each fixed point $\boldsymbol{p}^*$ is a local optimal solution for problem (P1). ■

E. Proof of Lemma 1

Given $\boldsymbol{x}\in\mathcal{X}$, let $c(r)$ denote the operating channel for reader $r\in\mathcal{R}$. That is, $x_{r,c(r)}=1$. From (16), exactly one of the entries $x_{r,1},\ldots,x_{r,C}$ is equal to 1. From (9), we have

$$P_r^{\text{succ}}(\boldsymbol{p})=\left(\prod_{n\in\mathcal{S}_r}\left(1-\gamma_{r,n}p_{n,c(n)}\right)\right)\left(p_{r,c(r)}\left(\prod_{m\in\mathcal{I}_r}(1-\gamma_{r,m}p_{m,c(m)})\right)\right). \tag{29}$$

Since for any $\alpha>0$, utility f_α is an increasing function, problem (Primal-P2) is equivalent to

$$\begin{aligned}\underset{\boldsymbol{p}\in\mathcal{P}(\boldsymbol{x}),\,\boldsymbol{\delta}>\mathbf{0}}{\text{maximize}}\quad & \sum_{r\in\mathcal{R}} f_\alpha(\delta_r)\\ \text{subject to}\quad & \delta_r\le\left(\prod_{n\in\mathcal{S}_r}\left(1-\gamma_{r,n}p_{n,c(n)}\right)\right)\left(p_{r,c(r)}\times\left(\prod_{m\in\mathcal{I}_r}(1-\gamma_{r,m}p_{m,c(m)})\right)\right),\ \forall r\in\mathcal{R},\end{aligned} \tag{30}$$

where $\boldsymbol{\delta}=(\delta_r,\ \forall\, r\in\mathcal{R})$. Problem (30) is still non-convex because of the product forms in the constraints. For each reader $r\in\mathcal{R}$, we define $\tilde{\delta}_r=\log(\delta_r)$. We also define:

$$\tilde{f}_\alpha(\tilde{\delta}_r)=f_\alpha(\exp(\tilde{\delta}_r))=-\alpha^{-1}(\exp(\tilde{\delta}_r))^{-\alpha}. \tag{31}$$

Clearly, $\tilde{f}_\alpha(\tilde{\delta}_r)=f_\alpha(\delta_r)$. Thus, problem (30) becomes

$$\begin{aligned}\underset{\boldsymbol{p}\in\mathcal{P}(\boldsymbol{x}),\,\tilde{\boldsymbol{\delta}}>\mathbf{0}}{\text{maximize}}\quad & \sum_{r\in\mathcal{R}}\tilde{f}_\alpha(\tilde{\delta}_r)\\ \text{subject to}\quad & \tilde{\delta}_r-\sum_{n\in\mathcal{S}_r}\log(1-\gamma_{r,n}p_{n,c(n)})-\log(p_{r,c(r)})\\ & -\sum_{m\in\mathcal{I}_r}\log(1-\gamma_{r,m}p_{m,c(m)})\le 0,\quad\forall r\in\mathcal{R},\end{aligned} \tag{32}$$

All constraints in problem (32) are convex. Moreover, $\tilde{f}_\alpha(\tilde{\delta}_r)$ is concave in $\tilde{\delta}_r$. Therefore, problem (32) is a convex problem with zero duality gap and a unique stationary point. Since problems (32), (30), and (Primal-P2) are equivalent, the same statements are true for problem (Primal-P2). ■

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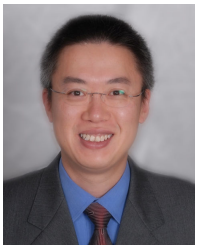
Amir-Hamed Mohsenian-Rad (S04-M09) received his B.Sc. degree from Amir-Kabir University of Technology (Tehran, Iran) in 2002, M.Sc. degree from Sharif University of Technology (Tehran, Iran) in 2004, and Ph.D. degree from The University of British Columbia (Vancouver, Canada) in 2008, all in electrical engineering. From March to July 2007, he was also a visiting scholar at Princeton University (Princeton, NJ). Currently, Dr. Mohsenian-Rad is a post-doctoral research and teaching fellow at the University of British Columbia. As a graduate student, he granted the UBC Graduate Fellowship as well as the Pacific Century Graduate Scholarship from the British Columbia Provincial Government. He is also the recipient of the prestigious Natural Sciences and Engineering Research Council of Canada (NSERC) fellowship. Dr. Mohsenian-Rad has serves as technical program committee (TPC) member for the IEEE Global Communications Conference (Globecom), the IEEE International Conference on Communications (ICC), the IEEE Vehicular Technology Conference (VTC), and the IEEE Consumer Communications and Networking Conference (CCNC). His research interests are in the area of optimization and game theory and their applications in computer communications and wireless networking.

Vahid Shah-Mansouri (S'02) received the B.Sc. and M.Sc. degrees in electrical engineering from University of Tehran, Tehran, Iran in 2003 and Sharif University of Technology, Tehran, Iran in 2005, respectively. From 2005 to 2006, he was with Farineh-Fanavar Co., Tehran, Iran. He is currently working towards the Ph.D. degree in the Department of Electrical and Computer Engineering at the University of British Columbia (UBC), Vancouver, BC, Canada. As a graduate student, he received the UBC Four Year Fellowship and UBC Faculty of Applied Science Award. His research interests are in design and mathematical modeling of RFID systems and wireless networks.



Vincent W.S. Wong (SM'07) received the B.Sc. degree from the University of Manitoba, Winnipeg, MB, Canada, in 1994, the M.A.Sc. degree from the University of Waterloo, Waterloo, ON, Canada, in 1996, and the Ph.D. degree from the University of British Columbia (UBC), Vancouver, BC, Canada, in 2000. From 2000 to 2001, he worked as a systems engineer at PMC-Sierra Inc. He joined the Department of Electrical and Computer Engineering at UBC in 2002 and is currently an Associate Professor. His research areas include protocol design, optimization, and resource management of communication networks, with applications to the Internet, wireless networks, RFID systems, and intelligent transportation systems. Dr. Wong is an Associate Editor of the IEEE Transactions on Vehicular Technology and an Editor of KICS/IEEE Journal of Communications and Networks. He serves as TPC member in various conferences, including IEEE Infocom, ICC, and Globecom. He is a senior member of the IEEE and a member of the ACM.

Robert Schober (M'01, SM'08, F'10) was born in Neuendettelsau, Germany, in 1971. He received the Diplom (Univ.) and the Ph.D. degrees in electrical engineering from the University of Erlangen-Nuermberg in 1997 and 2000, respectively. From May 2001 to April 2002 he was a Postdoctoral Fellow at the University of Toronto, Canada, sponsored by the German Academic Exchange Service (DAAD). Since May 2002 he has been with the University of British Columbia (UBC), Vancouver, Canada, where he is now a Full Professor and Canada Research Chair (Tier II) in Wireless Communications. His research interests fall into the broad areas of Communication Theory, Wireless Communications, and Statistical Signal Processing.

Dr. Schober received the 2002 Heinz MaierLeibnitz Award of the German Science Foundation (DFG), the 2004 Innovations Award of the Vodafone Foundation for Research in Mobile Communications, the 2006 UBC Killam Research Prize, the 2007 Wilhelm Friedrich Bessel Research Award of the Alexander von Humboldt Foundation, and the 2008 Charles McDowell Award for Excellence in Research from UBC. In addition, he received best paper awards from the German Information Technology Society (ITG), the European Association for Signal, Speech and Image Processing (EURASIP), IEEE ICUWB 2006, the International Zurich Seminar on Broadband Communications, and European Wireless 2000. Dr. Schober is also the Area Editor for Modulation and Signal Design for the IEEE Transactions on Communications.