A UHF RFID-Based System for Children Tracking

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***Abstract*—Given the fact that roughly 800 000 children are reported missing in the United States every year, how to assist parents to track their children becomes an important problem. Even though many children tracking systems have been proposed, the high cost and energy limitation of locators are the stumbling blocks which limit the application of those systems. To address this challenge, we design a children tracking system based on RFID technology, where children carry RFID tags and the system is responsible for locating the children by aggregating the readings from the deployed readers. Noting the importance of localized processing for efficient children tracking, we further study how the locally available computing resource, such as the mobile devices carried by the park employees and visitors, can be utilized for service provisioning. Since mobile devices have limited energy, we study an energy efficiency optimization problem by jointly considering the resource allocation and user association. The formulated problem is solved by a dynamic updating matching approach. Through extensive simulations, we have demonstrated the effectiveness of our proposed solution.**

***Index Terms*—Energy efficiency (EE), RFID, tracking children.**

I. Introduction

LOSING a beloved child is no doubt the worst thing for every parent. In some cases, parents find that their children are lost while they are talking with others for a few seconds. Based on the statistical data for Missing and Exploited Children released by the National Center, we learn that roughly 800 000 children are missing every year in the United States, which means roughly 2000 children are reported missing every day [1]. Some incidents occur when parents take their children to public places, especially the markets, shopping malls, and theme parks. For example, in large theme parks like Walt Disney World, there are tens of thousands of visitors every day. It may be just a turn-around and the next thing you realize is that your child is missing. To make matters worse, finding a missing child in a huge park is almost impossible.

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To prevent parents from losing their beloved children, researchers have developed many systems and approaches. The most popular one is to place the global positioning system (GPS) locators on their children. The Paw tracker, Trax GPS tracker, and HEREO GPS watch [2] are the popular products based on GPS. The main issues of using GPS systems are high cost and energy limitation of a locator. When a GPS locator works in a continuous mode, it consumes energy rapidly. Thus, Bluetooth low energy (BLE) is emerging as the alternative approach to solve the children missing problem. In the BLE tracking systems, the locator can directly communicate with a user's device (e.g., smartphone). As mentioned in [3] and [4], a Bluetooth tracker company named Chipolo can help parents locate their children by attaching BLE tags to children's shoes or clothes. Even though the energy consumption has been reduced using BLE tags, the energy problem still limits the popularity of BLE tracking systems. Another drawback of the systems relying on BLE is that if the children go out of the communication range, their parents may not locate their children any more. Given the weakness mentioned above, it is imperative to design a new children tracking system, which is energy efficient and robust to dynamically changing environments.

Nowadays, RFID technology [5], [6], especially the passive RFID, which relies on the backscatter technology, has emerged as a promising approach due to its low cost and less restriction on energy. Lin *et al.* [7] constructed an RFID-based opportunistic network to locate children. They use distributed nodes to store the location data of tags. In their design, the system relies on moving people, who acts as carry-and-forward nodes to transmit data. When users query the information of tags, the control center can find the corresponding information in the distributed storage nodes. Chen [8] have proposed another system that combines RFID networks with wireless sensor networks for tracking children in theme parks. In their design, the readers rely on the wireless sensor networks for data transmissions.

However, there are several challenges facing RFID-based children tracking system. First, potential congestion would reduce quality of service. Most of RFID-based children tracking systems adopt the centralized design. In this design, a reader would transmit collected data to the remote control center (such as a base station) for processing and storage. For example, the proposed system in [8] is designed in the centralized fashion. In their design, reading data would be relayed back to the remote control center through multihop wireless sensor networks. Actually, the remote control center would be congested due to all of devices waiting for transmitting and computing data in its coverage. Second, unnecessary waste of communication resource is another problem. Most of the situations, the readers would operate in the continuous model. The continuously reading may incur significant traffic. Notice that it is not necessary to transmit reading data all the time to remote control center since children might stay in the same place, such as waiting in line for a spot of interest in a theme park. Third, full coverage of children activity area is critical. In the design of Lin *et al.* [7] and Chen [8], they both propose to simply place the fixed readers in key points. Without full coverage of children activity area, the system may have the blind area. As a result, it is critical to design an efficient and effective RFID-based children tracking system.

Inspired by previous works, we propose a new children tracking system based on UHF RFIDs (as shown in Fig. 1). Similar to previous works, we propose to fasten the passive RFID tags on children. When the children play in a theme park, their tags would be read by the nearby fixed readers with wireless communication capability. These fixed readers are deployed by a service provider, such as the theme park, to cover the whole activity area of children. The service provider obtains the locations of children by aggregating the readings of these readers. To avoid the potential congestion problem in the centralized design, we utilize the mobile devices carried by the park employees and visitors as the local processing units. In so doing, raw reading data is not sent to the remote control center for data processing. With the help of remote control center, the reader finds a mobile device (e.g., smartphone) for data processing. Then, the associated mobile device/local processing unit delivers the processed data to users. In practice, some of the users may locate in the communication range of associated mobile devices. Thus, the associated mobile devices directly transmit the data to the users in the transmission range. For the users out of the communication range of associated mobile devices, the remote control center serves as the relay for data transmissions. Since mobile devices have limited energy, if they consume too much of their energy quickly, there are not enough number of local processing units that support the service for users. To fully exploit the mobile devices for service provisioning, we formulate an energy efficiency (EE) optimization problem by jointly considering power allocation and user association. We address the EE optimization problem by adopting the dynamic updating matching (DUM) algorithm. As such, the main contributions of this paper are summarized as follows.

1) We propose a novel RFID system to track children in public areas. With the designed system, the locations of children can be tracked with simple carry-on devices, namely, RFID tags. We utilize the mobile devices carried by park employees and/or visitors as local processing units to avoid the potential congestion problem. With the help of remote control center, each reader is matched with a mobile device for data processing.
2) EE of mobile devices is critical in our scenario because of the energy limitation of associated mobile devices. We formulate an EE optimization problem by jointly considering the resource allocation and user association. Since the formulated EE problem is NP-complete, we adopt dynamic update matching algorithm to provide an suboptimal solution.
3) Through extensive simulations, we show that our proposed schemes are effective in improving the EE performance of associated mobile devices.

The rest of this paper is organized as follows. We discuss related work in Section II. In Section III, we introduce network configuration and corresponding models. According to those models, we formulate the optimization problem as fractional programming problem under multiple constraints in Section IV, We also introduce the dynamic matching approach to feasible solution in Section V. We evaluate the performance of the proposed scheme in Section VI, followed by concluding remarks in Section VII.

II. Related Work

We classify the existing applications for tracking children into three types. The Type-I applications [9]–[13] rely on GPS technology. Gupta and Harit [9] designed a system utilizing GPS, short messaging service (SMS), and smartphones. Smartphones as the locators are carried by the children, so they can send location information to the parents through the Internet. SMS plays as a backup option in the system. Once children enter the area where there is no Internet connection, the location information can be sent as a short message through the cellular networks. Even though the proposed system in [9] can easily track the children, it has several drawbacks. First, the large size of a smartphone makes it inconvenient to carry around for children. Second, the smartphone has energy limitation. Third, there is a high risk of losing the smartphone, which leads to the failure of the system.

The Type-II applications [9], [14]–[16] employ the Bluetooth technology. A tracking system using Bluetooth mobile ad hoc network (MANET) has been proposed in [15]. In the scenario of Morii *et al.*, every target child has an android terminal, which can autonomously configure a wireless network based on autonomous clustering technique. Android terminals in the cluster communicate with each other to collect group information. As a result, each parent can check whether his/her child becomes alone or not. In addition, parents also receive the current locations of their children. In [15], they design two-tier networks to support the system. The first tier is a Bluetooth MANET, which can easily form a group. The second tier is the mesh networks that deliver the data from the group to the Internet. However, this system still has its own limitations, such as large device size, limited device energy, and heavy reliance on the Internet. Liu and Li [14] proposed a BLE tag-based system that utilizes the limited communication range between the locator and the receiver. The devices (e.g., smartphone) carried by users keep receiving signals from BLE tags as long as the children stay in the safety range (e.g., communication range) of the users (e.g., parents of the children). Once losing the communications from the locators, the users' devices get an alert. To overcome the weakness that the system may fail to work when children disappear from the range, Liu and Li [14] designed a collaborative approach to

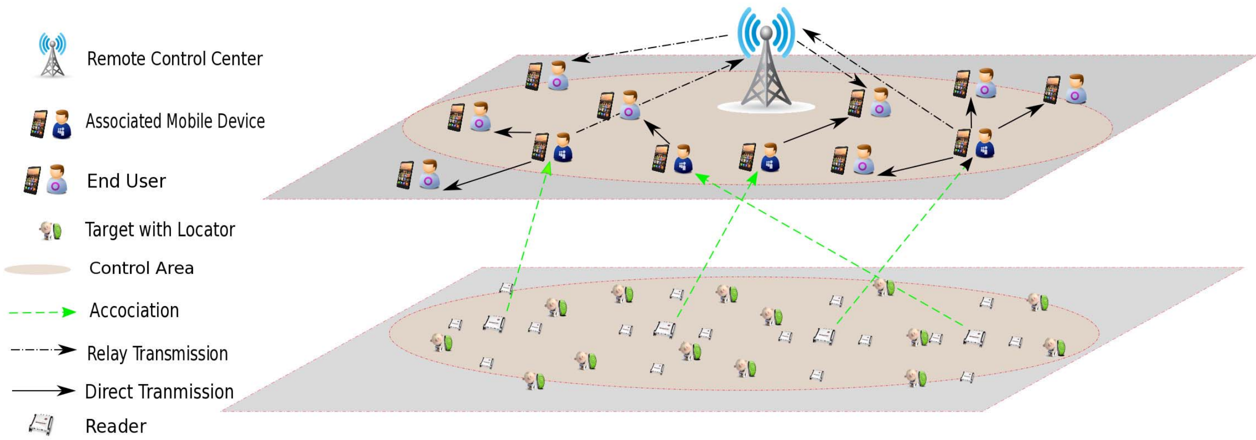

Fig. 1. System architecture.

finding the lost children. However, the limited energy problem of BLE tags remains unsolved.

The Type-III applications construct RFID networks to track children. According to the scheme of Lin *et al.* [7], RFID readers are deployed in key areas to monitor tags (which are attached to children) passing by. Depending on the location, readers can choose to either directly transmit data to nearby storage node or rely on packet passing nodes (e.g., visitors or employees) to deliver the data. The major problem of this RFID system is that the packet nodes may lead to a long delay in sending the data to the nearby storage node. To overcome this weakness, Chen [8] created a scenario in which RFID readers are placed in the landmarks of a theme park, making it easier to keep monitoring the children when they play around the landmarks. The wireless sensor networks would subsequently transmit the data to the gateway. However, the coverage is a serious problem in this scenario.

III. System Architecture

A. Overview

Fig. 1 gives a high-level overview of our proposed system. RFID tags are attached to the visitors of theme parks. We call the tag attached on child is the target tag and the tag placed on a normal visitor is the interference tag. In addition, we also deploy RFID reference tags which can help readers locate target tags more easily. RFID readers are deployed in theme parks to make sure that every point of the children's activity area is covered at least by one reader. We also assume that readers are equipped with communication radio interface with other mobile devices, which can be done with certain customization. When children travel in the theme parks, the attached tags will be scanned by the nearby fixed RFID readers. As we mentioned in the previous section, we employ the wireless communication readers. Then, readers send the scanned data to local processing units for data processing. Local processing units are the mobile devices carried by park employees and visitors. Actually, visitors can access this system via an application which is downloaded and installed on their mobile devices. Parents can track their children through this application. If the smartphone of a visitor has enough power, the visitor can apply as the local processing unit to perform processing and get monetary compensation. Finally, local processing units send the processed data to devices of users.

We divide the time into discrete fixed time period, called slot. At the beginning of the slot, readers first scan its coverage area to read data from tags in the area. The reader utilizes power control to tune the transmission power level in order to read the tags since power control not only helps improve the location accuracy of target tags, but also avoids the reading collision problem among readers. We group readers into clusters. In each cluster, one central reader acts as the cluster head to gather reading data of all other readers. The cluster head also has ability to buffer the reading data. Then, the cluster heads gather all the raw reading data from their cluster members.

The raw reading data will go through two stages before being delivered to the users. The first stage is the processing stage, which includes reference tag elimination, target tag location estimation, and so on. In the beginning of processing stage, all cluster heads request the remote control center help them find the local processing units. At the same time, the remote control center requires information of all mobile devices registered as the candidates of local processing units. The reader-mobile device association process will be finished at the remote control center. Then readers send the raw reading data to the associated mobile device (e.g., d_1 in Fig. 2). The raw reading data will be locally processed by the associated mobile devices. Then, the processed data is passed to the second stage, the delivery stage. In this system, we assume both readers and mobile devices have limited device to device communication range. In the delivery stage, the associated mobile devices directly transmit the processed data to the nearby end users (e.g., d_2 and d_3 in Fig. 2) in its communication range. For the end users out of the communication range of the associated mobile device (such as d_4 in Fig. 2), the remote control center serves as the rely nodes for data transmissions. In addition, in the subsequent development of this paper, when we say

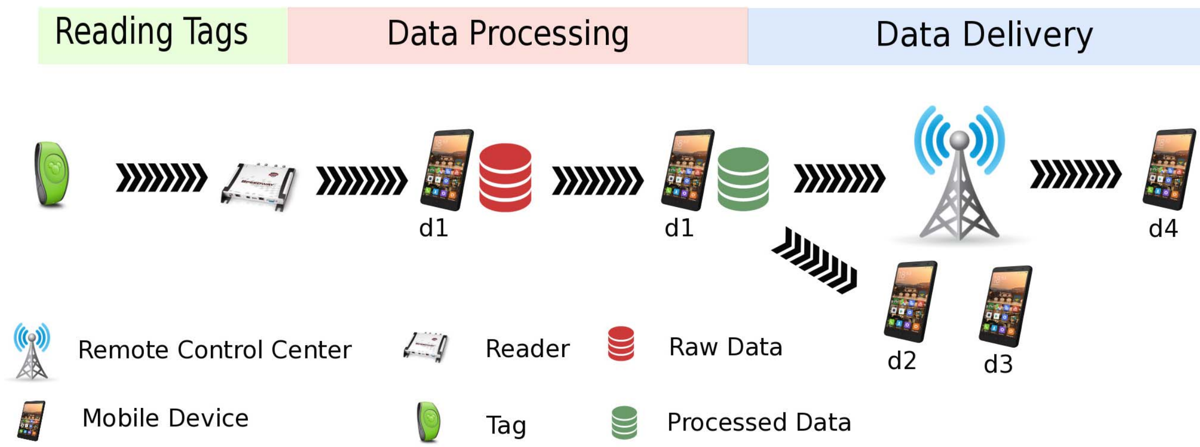

Fig. 2. Whole process of data processing and transmissions.

the reader, we mean the head of a reader cluster. The whole process are summarized in Fig. 2.

B. System Model

We denote the set of the readers as $\mathcal{R} = \{1, 2, \ldots, j, \ldots, R\}$, the jth reader by r_j. We also denote the mobile devices by $\mathcal{D} = \{1, 2, \ldots, i, \ldots, D\}$, the ith mobile device by d_i. To evaluate the performance of our system, we first elaborate a few important concepts we will use in the subsequent development.

1) Link Data Rate: In our scenario, orthogonal channels are adopted in the transmissions among mobile devices and transmissions from mobile devices to remote control center. Thus, transmissions among different channels are interference free. According to the Shannon–Hartly theorem, the data rate of the link between mobile device d_i and mobile device d_k or remote control center B is

$$c_{i,\times} = W_{i\times} \log_2\left(1 + \frac{p_{i,\times} h_{i,\times}}{N_0 W_{i,\times}}\right) \tag{1}$$

where $\times$ indicates a target node (either d_k or base station B), and $p_{i,\times}$ denotes the transmission power of mobile device d_i, $h_{i,\times}$ is the channel gain from mobile device d_i to d_k or base station B, and N_0 is the power spectral density of additive white Gaussian noise. Then, we can get the total achieved data rate via the mobile device d_i is

$$C_i = \sum_{k \in \mathcal{T}_i \cup B} W_{i,k} \log_2\left(1 + \frac{p_{i,k} h_{i,k}}{N_0 W_{i,k}}\right) \tag{2}$$

where $\mathcal{T}_i$ is the set of neighboring nodes, which means the end users within i's transmission range. For example, in Fig. 2, the set of neighboring nodes of mobile device d_1 is $\{d_2, d_3\}$ since only these destinations/end users in its communication range. $|\mathcal{T}_i|$ is the cardinality of the set $\mathcal{T}_i$. Actually, $\mathcal{T}_i$ is determined by the reader association selection $x_{j,i}$. That is, when mobile device d_i associates with different reader r_i, the set $\mathcal{T}_i$ is different.

2) Power Consumption: The total power consumption of each mobile device d_i includes two parts, which are the aggregated power consumption for data processing E_i^P and the power consumption for data transmissions, respectively.

TABLE I
TABLE OF PARAMETERS

Parameter	Description
$\mathcal{R}$	Set of readers
$\mathcal{D}$	Set of mobile devices
r_j	j-th fiexd reader
d_i	i-the mobile device
$P_{i,\times}$	Transmission power of the mobile device d_i
$h_{i,\times}$	Channel gain
N_0	Power spectral density of additive white Gaussian noise
$\mathcal{T}_i^j$	Set of connected devices within d_i's transmission range
E_i^P	Power consumption for data processing of d_i
P_i^{cir}	Circuit power consumption
η	Power amplifier efficiency

We define f_i as the computation ability of mobile device d_i. The power consumption of mobile device d_i for data processing can be calculated as [17]

$$E_i^P = \kappa (f_i)^3 \tag{3}$$

where κ is the coefficient depending on the chip architecture. Power consumption for data transmissions can be characterized by [18]

$$E_i^{\mathrm{TR}} = \sum_{k \in \mathcal{T}_i \cup B} \eta p_{i,k} + P_i^{\mathrm{cir}}. \tag{4}$$

Here, P_i^{cir} is denoted as the circuit power consumption and η is the power amplifier efficiency. The power consumptions of the infrastructure nodes and fixed readers are assumed not to be considered as all of them are powered by more powerful external power source.

3) Matching Matrix: We introduce an $R \times D$ reader association matrix. Element $x_{j,i}$ in the matrix indicates whether or not the reader r_j is associated with mobile device d_i. That is, fixed reader r_j transmits the raw data to mobile device d_i for processing when $x_{j,i} = 1$; otherwise, $x_{j,i} = 0$.

To improve the clarity, notations of key parameters are summarized in Table I.

IV. Problem Formulation

Given the model described before, we target at the problem on maximizing the EE of associated mobile devices. In our design, sufficient number of available local processing units can provide long and stable service for users. However, if all mobile devices consume their energy quickly, there are few mobile devices would act as local processing units to support users. Thus, improving EE of mobile devices can maintain quality of experience and make the whole system stable [19]. Hence, we consider a joint EE optimization problem for reader association decision and resource allocation. We first formulate the EE function for each mobile device d_i, which is given by

$$\mathrm{EE}_i = \frac{C_i}{E_i^P + E_i^{\mathrm{TR}}} \tag{5}$$

where C_i is the total achieved data rate via mobile device d_i to users (mobile devices carried by parents). That is to say, data from readers is processed on mobile device d_i, and then the processed data is sent to users. To process data $C_{j,i}$ for users, mobile device d_i consumes a certain amount of power, which includes the power consumption for data processing E_i^P and the power consumption for data transmissions E_i^{TR}.

Furthermore, we need to consider several constraints for the EE optimization problem.

Reader Association: The fixed reader r_j can only associate with one mobile device for data processing. This constraint can be captured as follows:

$$\sum_{i \in \mathcal{N}} x_{j,i} = 1. \tag{6}$$

Maximum Power Limitation: In our scenario, we assume each mobile device can just utilize transmission power below the maximum $P_{\max}$, that is,

$$p_{i,k} \le P_{\max}, \quad k \in \mathcal{T}_i \cup B. \tag{7}$$

QoS Requirement: In order to guarantee the QoS requirement for the users, we introduce the constraint as

$$W_{i,k} \log_2\left(1 + \frac{p_{i,k} h_{i,k}}{N_0 W_{i,k}}\right) \ge c_{\min}, \quad k \in \mathcal{T}_i \cup B \tag{8}$$

where $c_{\min}$ is denoted as the QoS threshold.

A. EE Optimization

Based on the constraints we mentioned above, we have the following optimization problem:

$$\begin{aligned}
\max_{x_{j,i}, p_{i,k}} \quad & \sum_{i \in N} \frac{\sum_{j \in M} x_{j,i} \omega_i C_{j,i}}{|\sum_{j \in M} x_{j,i}| E_i^P + \sum_{i \in M} x_{j,i} E_{j,i}^{\mathrm{TR}}} \\
\text{s.t.} \quad & C_{j,i} = \sum_{k \in \mathcal{T}_{j,i} \cup B} W_{i,k} \log_2\left(1 + \frac{p_{i,k} h_{i,k}}{N_0 W_{i,k}}\right) \\
& E_i^{\mathrm{TR}} = \sum_{k \in \mathcal{T}_{j,i}} \eta p_{i,k} + P_i^{\mathrm{cir}} \\
& E_i^P = \kappa (f_i)^3 \\
& 0 \le p_{i,k} \le P_{\max}, \quad k \in \mathcal{T}_{j,i} \cup B \\
& W_{i,k} \log_2\left(1 + \frac{p_{i,k} h_{i,k}}{N_0 W_{i,k}}\right) \ge c_{\min}, \quad k \in \mathcal{T}_{j,i} \cup B \\
& \sum_{i \in \mathcal{N}} x_{j,i} = 1 \\
& x_{j,i} \in \{0, 1\}
\end{aligned} \tag{9}$$

where ω_i is a balancing weighting factor related to the residual energy of mobile device d_i and the stable time. Actually, if a mobile device has more residual energy and does not move frequently, it would be a better choice to be a local processing unit. Here, $\mathcal{T}_{j,i}$ is device d_i's neighboring nodes that request the data from reader r_j. Clearly, our formulated optimization problem (9) is a mixed-integer nonlinear programming problem, which is NP-complete as proved in [20]. In the next section, we adopt matching theory to find the feasible solution to the EE maximization problem.

V. Matching Approach

Matching game is one of the popular distributed approaches to solving optimization problems. Different from centralized algorithms which may obtain optimal solutions with high computational complexity, distributed approaches typically achieve suboptimal results with lower complexity. Actually, we contend that matching game is an semi-distributed approach by reasoning that many operations in the matching approach, such as local information gathering, preference list establishment, and decision making are performed in a distributed fashion, while other operations may depend upon global information from a centralized coordinator. In this section, we introduce the matching approach to solving the EE maximization problem (9).

A. Matching Concepts

We first define a matching between two finite and disjoint sets denoted by $\mathcal{M} = \{m_1, \ldots, m_i, \ldots, m_p\}$ and $\mathcal{W} = \{w_1, \ldots, w_j, \ldots, w_q\}$, respectively. Each $m_i \in \mathcal{M}$ has a utility over the set $\mathcal{W}$ and the same as $w_j \in \mathcal{W}$. The value of utility represents the preference relations of each individual. For example, if m_i prefers w_j to w_k, we write it as $w_j \succ_{m_i} w_k$. Given preferences, we give the following formal matching definition.

Definition 1: A one-to-one matching μ is a mapping from the set $\mathcal{M}$ to $\mathcal{W}$, such that $\mu(m_i) = w_j$ if only if $\mu(w_j) = m_i$. Moreover, $\mu(m_i) \in \mathcal{W}$ and $\mu(w_i) \in \mathcal{M}$.

Once a matching μ is established, we need to check the stability of μ. If no agent (m_i or w_j) wants to change its current paired assignment, a matching is stable. The definition of stability is provided in Definition 2.

Definition 2: A matching μ is said to be stable if it admits no blocking pairs. A pair (m_i, w_j) is a blocking pair if the following the conditions hold: 1) m_i is either unassigned or prefers w_j to $\mu(m_i)$ and 2) w_j is either unassigned or prefers m_i to $\mu(w_j)$.

B. Preference Establishment

We first establish each player's preference list. Notice that mobile devices' preference lists cannot be set up since the neighboring nodes set $\mathcal{T}_{j,i}$ for each device d_i is unknown before the reader mapping decisions between readers and devices have been made. We consider the case of two adjacent time slots. Assume the network condition changes slightly because the time slot is short. That is to say, only a small number of readers' or mobile devices' preferences are changed. Under this assumption, we can set up mobile devices' preference lists of the current time slot according to the knowledge from previous slot.

Preference Establishment: The basic idea to establish the preference of a mobile device is to use knowledge from previous time period to obtain the set of neighboring nodes. We first set up the preference list of r_j. All readers establish their preference lists according to their benefit functions. The benefit of reader r_j depends on the achievable data transmission rate, which can be characterized as $\mu C_{j,i}$, where μ is the benefit factor. Without loss of generality, we set $\mu = 1$. Thus, the preference list of r_j over device d_i at time slot t is $\mathbf{V}_j^R(t) = (V_{j,i}^R(t))$, where $V_{j,i}^R(t)$ is obtained according to

$$V_{j,i}^R(t) = \omega_i \sum_{k \in \mathcal{T}_{j,i}(t-1) \cup B} W_{i,k} \log_2\left(1 + \frac{p_{i,k}(t) h_{i,k}(t)}{N_0 W_{i,k}}\right). \quad (10)$$

We now introduce the preference establishment of a mobile device. Mobile device d_i sets up its preference based on its transmission cost function. The cost function is the power consumption for transmissions and processing, which is $\nu(E_i^P + E_{j,i}^{\mathrm{TR}})$. Similarly, we also assume $\nu = 1$ for ease of presentation. Then the preferences of d_i over device r_j at time slot t is $\mathbf{V}_i^D(t) = (V_{i,j}^D(t))$ and $V_{i,j}^D(t)$ can be captured according to

$$V_{i,j}^D(t) = \kappa (f_i)^3 + \sum_{k \in \mathcal{T}_{j,i} \cup B} \eta p_{i,k}(t) + P_i^{\mathrm{cir}}. \quad (11)$$

We model d_i's preference and r_j's preference according to local maximum achievable EE with the set of neighboring nodes $\mathcal{T}_{j,i}(t-1)$ at time slot t. Thus, we develop the following fast iterative power allocation (FIPA) algorithm to obtain the transmission power between device d_i and neighboring nodes set $\mathcal{T}_{j,i}$, which is obtained from the formulated local power allocation problem

$$\begin{aligned} \max_{p_{i,k}} \quad & U_i^{\mathrm{EE}}(t) = \frac{C_i\big[p_{i,k}(t)\big]}{E_i\big[p_{i,k}(t)\big]} \\ \text{s.t.} \quad & C_i\big[p_{i,k}(t)\big] = \omega_i \sum_{k \in \mathcal{T}_{j,i}(t-1) \cup B} W_{i,k} \log_2\left(1 + \frac{p_{i,k}(t) h_{i,k}(t)}{N_0 W_{i,k}}\right) \\ & E_i\big[p_{i,k}(t)\big] = \kappa (f_i)^3 + \sum_{k \in \mathcal{T}_{j,i}(t-1) \cup B} \eta p_{i,k}(t) + P_i^{\mathrm{cir}} \\ & 0 \le p_{i,k} \le P_{\max} \quad \big(k \in \mathcal{T}_i \cup B\big) \\ & W_{i,k} \log_2\left(1 + \frac{p_{i,k} h_{i,k}}{N_0 W_{i,k}}\right) \ge c_{\min}, \quad k \in \mathcal{T}_i \cup B. \end{aligned} \quad (12)$$

Since the problem formulated in (12) is a nonlinear fractional programming, we first employ fractional programming theory to transform it to an equivalent convex programming. Thus, based on what Dinkelbach has elaborated in [21] and more recent studies [22], [23], we have the following proposition.

Algorithm 1 FIPA Algorithm

Input: c_{min}, P_{max},.
Output: $p_{i,k}(t)$
Initialization;
Δ,$\lambda(0)$,N,$n = 1$.
Power Allocation;
Calculate each $P_{i,k}^{min}$ according to (8)
while $n \le N$ **do**
  Obtain $\hat{p}_{i,k}(n)$ by (15)
  if $\hat{p}_{i,k}(n) < P_{i,k}^{min}$ **then**
    Set $\hat{p}_{i,k}(n) = P_{i,k}^{min}$
  end if
  if $\hat{p}_{i,k}(n) > P_{max}$ **then**
    Set $\hat{p}_{i,k}(n) = P_{max}$
  end if
  if $C_i[\hat{p}_{i,k}(n)] - \lambda(n-1)E_i[\hat{p}_{i,k}(n)] \ge \Delta$ **then**
    Set $\lambda(n) = C_i[\hat{p}_{i,k}(n)]/E_i[\hat{p}_{i,k}(n)]$;
  else
    $p_{i,k}(t) = \hat{p}_{i,k}(n)$
  end if
  Update $n = n + 1$
end while

Proposition 1 [21]: Define the function Q as

$$Q(\lambda) = \max_{p_{i,k}} C_i\big(p_{i,k}\big) - \lambda E_i\big(p_{i,k}\big). \quad (13)$$

Then, the optimal power allocation $p_{i,k}^*$ is achieved if and only if there is λ^* such that $Q(\lambda^*) = C_i(p_{i,k}^*) - \lambda^* E_i(p_{i,k}^*) = 0$.

From this result, we develop the following algorithm.

1) FIPA Algorithm: The equivalent optimization problem is given by

$$\begin{aligned} \max_{p_{i,k}} \quad & C_i\big(p_{i,k}\big) - \lambda^* E_i\big(p_{i,k}\big) \\ \text{s.t.} \quad & 0 \le p_{i,k} \le P_{\max}, \quad k \in \mathcal{T}_i \cup B \\ & c_{i,k} \ge c_{\min}, \quad k \in \mathcal{T}_i \cup B. \end{aligned} \quad (14)$$

Then we utilize FIPA algorithm based on the well-known Dinkelbach algorithm [21] to get the specific values of λ^*. At the nth iteration, with the value of $\lambda(n-1)$ from the $(n-1)$th iteration, $p_{i,k}(n)$ are obtained by

$$p_{i,k}(n) = \left[\frac{1}{\eta \lambda(n-1) ln2} - \frac{N_0 W_{i,k}}{h_{i,k}}\right]^+ \quad (15)$$

where $[x]^+ = \max\{x, 0\}$. Then, if $p_{i,k}(n) > P_{\max}$, we set value of $p_{i,k}(n)$ to $P_{\max}$. If $p_{i,k}(n) < P_{i,k}^{\min}$ [which is obtained from (8)], we set value of $p_{i,k}(n)$ to $P_{i,k}^{\min}$. Finally, if $C_i[\hat{p}_{i,k}(n)] - \lambda(n-1)E_i[\hat{p}_{i,k}(n)] < \Delta$ holds, the algorithm stops. Otherwise, update $n = n + 1$, $\lambda = C_i[p_{i,k}(n)]/E_i[p_{i,k}(n)]$, and go to the next iteration. The overall FIPA algorithm is summarized in Algorithm 1. We can also use more efficient algorithms developed in [22] and [23], but we choose Dinkelbach's algorithm for the ease of presentation.

C. Dynamic Updating Matching Algorithm

When the preference establishment is completed, we can start with the matching. We propose the DUM algorithm,

Algorithm 2 DUM Algorithm

Input: c_{min}, P_{max},P_{total},$\mathbf{V}_j^R(t)$,$\mathbf{V}_i^D(t)$, $\mathcal{R}$, $\mathcal{D}$.
Output: Matching $\mu(t)$
Initialization;
Get $p_{i,k}(t)$ by FIPA algorithm
Matching Construction;
Each r_j sets up its preference $\mathbf{V}_j^R$ according to (10)
Each d_i sets up its preference $\mathbf{V}_i^D$ according to (11)
Construct unmatched set $\mathcal{R}_{un}$, set $\mathcal{R}_{un}$=$\mathcal{R}$
Matching Construction;
while $\mathcal{R}_{un} \neq \emptyset$ **do**
  for each $r_j \in \mathcal{R}_{un}$ **do**
    Proposes to the first d_i in its preference list and remove d_i from $\mathbf{V}_j^R$;
  end for
  for $d_i \in \mathcal{D}$ **do**
    if d_i receives one proposal **then**
      d_i keeps the proposal;
      Remove r_j from $\mathcal{R}_{un}$;
    else
      d_i keeps the most preferred proposal from r_{j*}, and rejects the rest;
      d_i removes r_{j*} from the $\mathcal{R}_{un}$, and add the rejected readers into the $\mathcal{R}_{un}$;
    end if
  end for
end while
Update;
if $\mathcal{R}_{un} \neq \emptyset$ **then**
  Update preference list $\mathbf{V}_i^D$;
  Update preference list $\mathbf{V}_i^R$;
  Go to Stage 1;
end if

which proceeds iteratively. As summarized in Algorithm 2, the DUM algorithm has two stages. At the first stage, readers conduct the matching based on the preference list $\mathbf{V}_j^R$. In each iteration, reader r_i proposes to its most preferred device d_i. After this, d_i is removed from preference list $\mathbf{V}_j^R$. Then device d_i decides whether to accept or reject the proposal based on its preference list over the reader r_j. If there are more than one proposal, device d_i chooses to keep the reader r_j that it favors the most, and rejects the rest. The proposing and accepting/rejecting iterations run for as many rounds as needed until all readers are matched or all readers' preferences that are fully examined. We also consider the case all readers' preferences are fully examined but some readers are still unmatched. We let device d_i increase its accepting capacity and reader r_j updates its preference list based on the current matching. Then readers conduct the new matching based on the new preference lists. The overall DUM algorithm are given in Algorithm 2.

VI. Performance Evaluation

A. Simulation Setup

This section presents EE of the proposed solution. There are R readers placed in the grid topology and D mobile devices randomly distributed in the area. A snapshot of mobile device locations with $D = 70$ and reader locations with $R = 49$ is shown in Fig. 3. The big diamond is the remote control center, the stars are the RFID readers, and the dots are the mobile devices. We assume the communication range between mobile devices is up to 100 m. The mobile devices are assumed to have an circuitry power consumption $P_{\text{cir}} = 50$ mW. We also set the effective switched capacitance $\kappa = 10^{-28}$ [17]. The channel fading is modeled by complex normal distribution, $\mathcal{CN}(0, 1)$ [24].

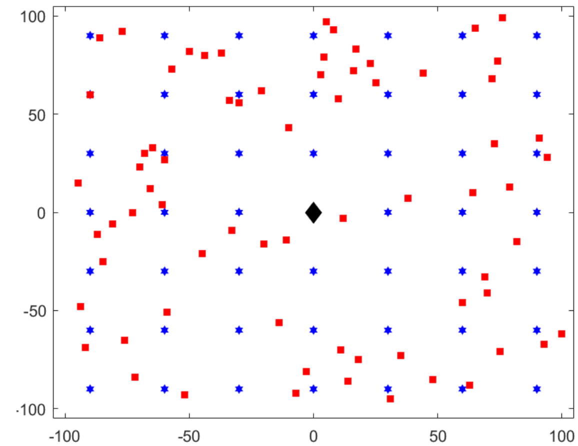

Fig. 3. Snapshot of mobile device location with $N = 70$.

To evaluate the performance, the proposed matching algorithm is compared with classical stable marriage matching (SMM) algorithm and one heuristic algorithm. The heuristic algorithm is called reader-greedy algorithm, which readers are always matched with the mobile devices most preferred according to readers' preferences. In addition, for the purpose of comparing the impact of our proposed power allocation approach, we also introduce random power allocation approach and greedy power allocation approach. In particular, greedy power allocation approach allocates the maximum transmission power $P_{\max}$ for every transmission link of associated mobile devices. Random power allocation approach employs transmission power distributed in the range $[0, P_{\max}]$.

B. Results and Analysis

1) Performance Comparison With the Optimal Solution: Fig. 4 shows EE performance of our proposed algorithm and the optimal solution, which serves as a benchmark for comparison. The optimal solution is obtained by the exhaustive enumeration method. Considering the high computational complexity of the exhaustive enumeration method, a small-scale network size is set to evaluate the performance of the proposed algorithm. We set the number of readers R is to be varied in [26] and the number of mobile devices is 5. As it is shown, the performance of proposed algorithm achieves more than 80% of the optimum one. Hence, we can conclude that DUM can attain an approximated optimal EE by comparing with the exhaustive enumeration scheme. Furthermore, although there is gap between DUM and the optimal matching

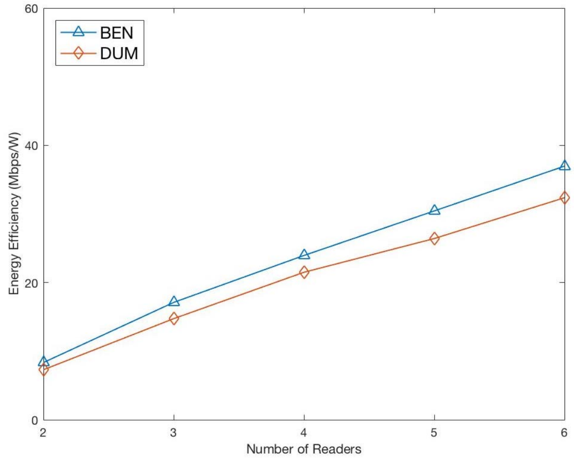

Fig. 4. Comparison to the optimal solution.

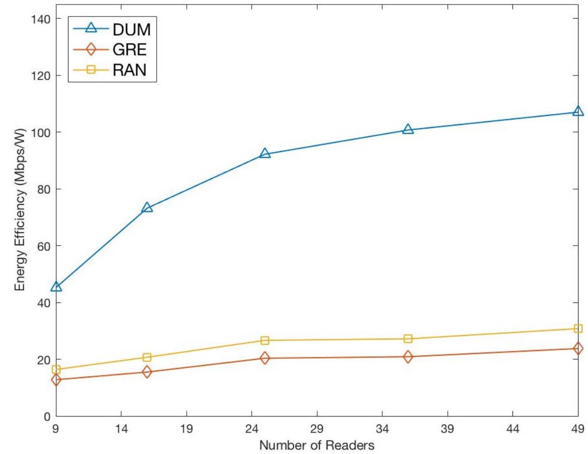

Fig. 6. Comparison of different power allocation approaches.

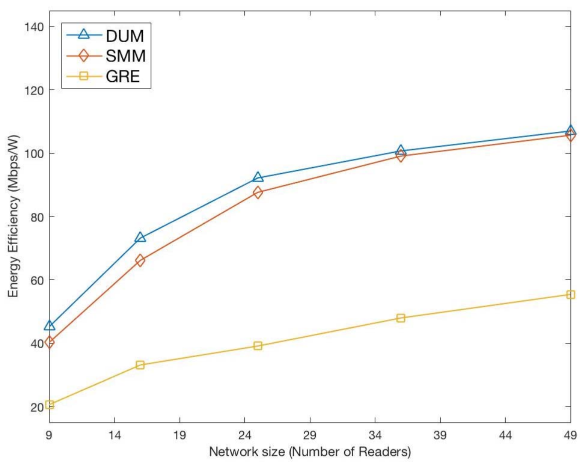

Fig. 5. Comparison of different matching algorithms.

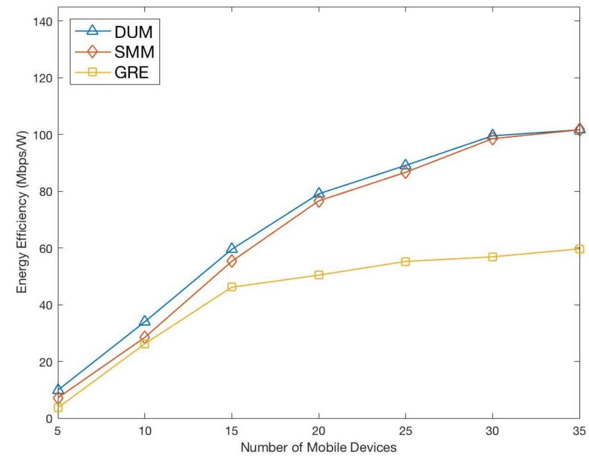

Fig. 7. EE under different density of mobile devices.

scheme, DUM can obtain a suboptimal performance with lower computational complexity.

2) Performance Comparison of Different Matching Algorithms: In Fig. 5, we evaluate the EE versus different network size. Since the readers are deployed in grid topology and have the fixed reading range, the number of readers varies with the network size. We assume that the number of readers R is varied in [949]. We set the density of mobile devices to be fixed, $\Omega = 0.005$ devices/m^2. Simulation results demonstrate that the EE of the proposed matching approach first increases fast and then grows slowly. The reason is that with the network size increasing, both readers and mobile devices have a wider variety of expanded matching candidates. In the three approaches, the proposed matching algorithm achieves the best EE, which indicates that it can exploit more benefits from the diverse choices than the other two algorithms. The performance of SMM algorithm is not as good as the proposed algorithm since it cannot update preference timely and ignores the benefits from the previous matching. The performance of the reader-greedy approach is not as good as the other two algorithms since it cannot fully exploit the diverse matching candidates and ignores the benefits from power allocation process of data transmissions.

3) Comparison of Power Allocation Approaches: Fig. 6 shows the EE of diffident power allocation strategies. We employ the same values of R and Ω as in the previous simulation. We set the maximum allocated power to $P_{\max} =$ 30 dBm. The result demonstrates that proposed power allocation approach achieves the best EE and outperforms the random power allocation approach and the greedy power allocation approach by 375% and 452% for $R = 25$, respectively. The random power allocation gets the second best performance since it has higher probability to take full advantage of the available power. We also find that benefits from the increasing power is not able to compensate for the EE loss. The greedy power allocation approach achieves the worst performance due to two reasons. The first is that the power allocation is fully ignored since it employs the fixed power. The second is that increasing transmission power has higher probability for passing the point for the optimum EE. Thus, increasing transmission power does not really improve the EE, rather causes significant EE loss.

4) EE With Respect to the Density of Mobile Devices: In Fig. 7, EE of different algorithms with respect to the varied density of mobile devices are evaluated. In this evaluation study, the density of mobile devices varying within [535] and

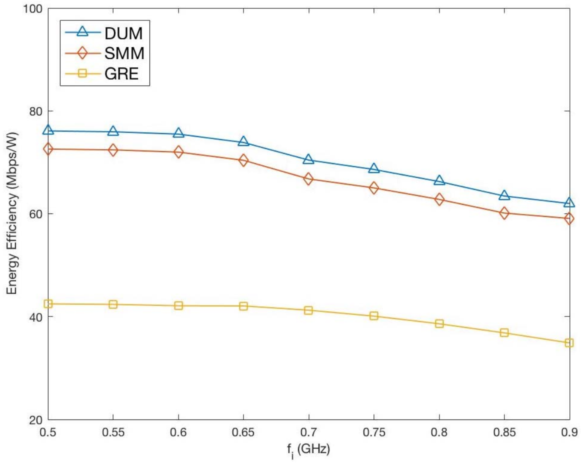

Fig. 8. EE under different computation capability of mobile device.

the step size is 5. We set the number of readers to $R = 36$. The result demonstrates that the impact of the density of mobile devices is evident only at lower values. When the density of mobile devices is not large, the EE grows almost linearly with the increasing density of mobile devices. Then, the EE stays nearly constant even when the density of mobile devices continues to increase. The reason is that when the density of mobile devices is small, the system gains more benefits from the density of mobile devices. Once density of mobile devices exceeds the point for the optimum EE, the reader can always be matched with perfect mobile devices to obtain the best EE.

5) EE With Respect to the Computation Capability of Mobile Device: We evaluate the EE versus different computation ability of mobile devices. In this evaluation study, the computation capability of mobile devices varies within [0.5 0.9] GHz and the step size is 0.05. We set the number of readers to $R = 16$. The results are shown in Fig. 8. It can be seen that three matching algorithms demonstrate the same relationship between EE and the computation capability of mobile devices. The result shows that the EE decreases nearly constant when the computation capability of mobile devices stays at low values. Then, the EE decreases evidently with the computation capability of mobile devices continues to increase. The reason is that when the computation capability of mobile devices is low, the system loses less benefits from the computation capability of mobile devices. That is to say the energy consumption of computing process is not dominant when the computation capability is low. Once the computation capability of mobile devices is high, computing process becomes the major source of energy consumption. Thus, the EE decreases evidently.

VII. Conclusion

In this paper, we have proposed a novel UHF RFID system for tracking children in the public area. In our RFID networks, readers are associated with mobile devices for target localization. With the help of remote central center, the reader is matched with an mobile device to transmit raw data for processing. Then, the associated mobile device deliver the processed data to the users. We formulate the EE optimization problem by jointly considering resource allocation and user association. To address the EE optimization problem, we have developed the DUM approach. Finally, we have demonstrated that the proposed DUM approach is an efficient way to enhance the performance of EE.

With the consideration of a practical environment of the UHF RFID tracking system, it is important to study the cost of matching process. Since in a practical environment, visitors have high mobility. When there is fewer stable mobile devices served as the local processing units, the system will frequently repeat the matching process between the readers and mobile devices. Thus, the computing and communication cost of matching process will increase. We will investigate, as part of our future work, the matching-cost efficient solution with the mobile devices of high mobility.

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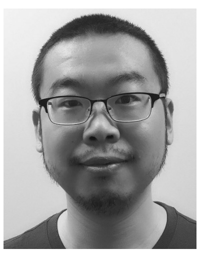

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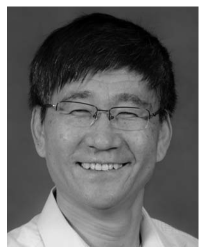

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