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A Joint Sensing and Communication Framework in Resource Constrained Mobile Edge Networks

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***Abstract*—Mobile crowd sensing (MCS) is a promising paradigm which leverages sensor-embedded mobile devices to collect and share data. To perform a sensing task in MCS, appropriate participating users are selected first, and efficient data sensing and transmission policies are then designed for data aggregation. In mobile edge networks, network resource availability affects how to select the participating users, and the bandwidth allocated to a user affects its process of data sensing and transmission. Since user selection, bandwidth allocation, data sensing and transmission are closely coupled issues in a resource constrained MCS system, we focus on designing a joint sensing and communication framework in this paper, by jointly optimizing the aforementioned four policies under resource constraints. Specifically, the optimal data sensing and transmission policies are first derived under a given user selection and bandwidth allocation scheme. Then the user selection and bandwidth allocation are optimized based on dynamic programming. Simulation results show that the proposed mechanism significantly outperforms several baseline solutions without considering wireless link vulnerability and/or resource limitations.**

***Index Terms*—Mobile crowd sensing, joint sensing and communication, user selection, bandwidth allocation.**

I. Introduction

Mobile crowd sensing (MCS) is an emerging sensing paradigm where human-carried devices are exploited to sense and collect various environmental information [1]. Compared to traditional sensing systems, MCS provides lower deployment cost, broader coverage and higher scalability. These advantages have enabled a wide range of MCS applications such as traffic planning, environment monitoring and commercial recommendations.

An MCS system consists of multiple mobile users acting as sensing service providers and an agent platform for sensing task allocation and sensed data aggregation. A typical MCS system is shown in Fig. 1, where the agent is deployed with the base station (BS) [2]. In MCS, a sensing task is fulfilled in the following three phases. Phase 1 is user selection (or task allocation), i.e., the agent assigns the sensing task to an appropriate set of mobile users based on certain task requirement. The selected users then sense the environment, collect and transmit the sensed data to the agent in phases 2 and 3 respectively.

In recent years, researchers have designed various strategies for user selection, data sensing and transmission in MCS [2]–[7]. For example, the user selection strategy is designed based on task requirement such as temporal and spacial coverage in [3] [4], or based on the remaining energy of device in [5]. In [6] [7], the data sensing and transmission policies are designed based on the incentive payments obtained or the movement trajectory of mobile users, while the process of sensing and transmission is optimized in [2] by finding the optimal sensing data size and transmit power for the sensing task. However, most of existing works focus on designing the user selection, data sensing and transmission policies separately, while assuming ideal network model without considering wireless resource constraints and link vulnerability.

Fig. 1. Illustration of an MCS system.

In practice, wireless bandwidth and energy resources are always limited, which significantly affects the process of MCS. Since the sensed data is transmitted for aggregation via wireless links, the limited bandwidth affects how many users can be selected for a sensing task, and the bandwidth allocated to a selected user affects its specific design of data sensing and transmission policies. Moreover, the available energy at the device determines whether to participate in the sensing task, and the data sensing and transmission policies at the device, in turn, affect the energy consumption.

From the process of MCS, we notice that sensing user selection, bandwidth allocation, data sensing and transmission jointly affect the resource efficiency and MCS performance and are thus coupled issues. Intuitively, separate design of the four individual policies cannot achieve optimality of system performance. This observation inspires us to develop a joint sensing and communication framework in a resource constrained MCS system, by jointly designing the aforementioned four policies. Such a co-design of sensing and communication has not been well addressed in existing works. Especially, resource limitation is not considered in most of relevant investigations. Although some works such as [2] [5] [6] have taken energy limitation into consideration, the wireless bandwidth limitation and allocation are not considered. Our key contributions are summarized as follows.

- We design a joint sensing and communication framework for implementing crowd sensing over resource-constrained wireless networks, where the wireless bandwidth constraint, bandwidth allocation, and energy limitation are jointly considered in designing the MCS system.
- In the developed framework, a joint optimization problem is formulated to simultaneously find the optimal set of participants for each sensing task, the bandwidth allocated to each participant, the data sensing and transmission policies at each participant (determined by the sensing data size and transmit power), with the aim of maximizing the performance of sensing task.
- To solve the optimization problem, we first derive the optimal sensing data size and transmit power under a given user selection and bandwidth allocation scheme. The original optimization problem is then transformed to a resource allocation problem, and dynamic programming is then used to optimize the user selection and bandwidth allocation. Simulation results demonstrate that the proposed mechanism provides significant performance improvements as compared to several baseline solutions.

II. System Model

We consider an MCS system consisting of a cellular BS and and N mobile users, where an MCS agent is deployed at the BS, as shown in Fig. 1. The system model is detailed below.

A. MCS Operation

In underlying model, each mobile user periodically reports its parameters including channel gain and available energy to the agent [2] [8]. For each sensing task arrived, the policies of user selection, bandwidth allocation, data sensing and transmission will be jointly determined by the agent based on the sensing task requirement, available network resources and users' current state. The process of performing a sensing task consists of three phases, i.e., task allocation, data sensing and transmission, as shown in Fig. 1.

In the *task allocation phase*, the agent selects a set of users for the sensing task, allocates certain amount of wireless bandwidth to these users, and informs each selected user its sensing data size and transmit power for this task. The objective is to maximize the performance of sensing task, or the utility of sensed data contributed by all participants.

In the *data sensing phase*, the selected users collect the data via their sensor-deployed devices in parallel. The energy consumed at a user for data sensing is proportional to the size of data collected by the user. That is why the agent optimizes the sensing data size based on devices' energy budget in the task allocation phase.

Finally, in the *data transmission phase*, each selected user transmits its sensed data to the agent based on the allocated bandwidth and optimized transmit power. Parallel data transmission is enabled via some channel partitioning scheme, such as frequency division multiple access (FDMA) technique.

There are three constraints in MCS, namely time, energy and bandwidth constraints. We consider time sensitive sensing tasks [2]–[4] where data sensing and transmission must be completed within a given threshold T. Let the time used for data sensing and transmission at user i be t_i^s and t_i^t, respectively. Then the time constraint is expressed as

$$t_i^s + t_i^t \leq T, \tag{1}$$

where the time required for the agent to inform the selected users their sensing and transmission parameters can be ignored since the size of these control messages is small. The second constraint is the energy limitation at the device, i.e.,

$$E_i^s + E_i^t \leq E_i, \tag{2}$$

where E_i, E_i^s and E_i^t are the available energy, the energy consumed for data sensing and transmission at user i, respectively.

Finally, the bandwidth constraint is that the total bandwidth allocated to the users cannot exceed the total available bandwidth B in the wireless network, or

$$\sum_i B_i \leq B, \tag{3}$$

where B_i is the bandwidth allocated to user i.

B. Bandwidth Allocation Model

Let binary variable l_i denote whether or not user i is selected for the sensing task. When $l_i = 1$, certain amount of wireless bandwidth must be allocated to it for data transmission. Since it is impossible to allocate arbitrary bandwidth to a user [9], we define a minimum bandwidth unit B_{min} and require the bandwidth allocated to user i (i.e., B_i) is an integer multiple of B_{min}. In other words, $B_i = k_i \cdot B_{min}$, where $k_i = 0, 1, 2, \cdots, \lfloor B/B_{min} \rfloor$.

The value of k_i determines the number of bandwidth units allocated to user i, and the relationship between k_i and l_i is

$$l_i = \lceil k_i / B \rceil, \tag{4}$$

which indicates that $l_i = 0$ if $k_i = 0$, and $l_i = 1$ if $k_i > 0$. To guarantee the total bandwidth allocated to the users do not exceed the total available bandwidth B, we have that

$$\sum_{i=1}^{N} k_i \cdot B_{min} \leq B, \tag{5}$$

$$0 \leq k_i \leq \lfloor B/B_{min} \rfloor, \ k_i \in \mathbb{Z}_0^+. \tag{6}$$

C. Data Sensing Model

When user i is selected for the sensing task (i.e., $l_i = 1$), its specific sensing data size z_i for this task will be informed by the agent, and the relationship between z_i and l_i is

$$0 \leq z_i \leq \lambda l_i, \tag{7}$$

which indicates that $z_i = 0$ if $l_i = 0$ and $z_i \geq 0$ if $l_i = 1$.

Let o_i denote the output data rate of user i [2]. Given the sensing data size z_i, the sensing time duration t_i^s at user i is

$$t_i^s = z_i/o_i, \tag{8}$$

and the energy consumed at user i for data sensing (or E_i^s) is

$$E_i^s = e_i \cdot z_i, \tag{9}$$

where e_i is the sensing energy consumption per bit [2].

D. Data Transmission Model

In MCS, each selected user needs to transmit its sensed data to the agent. Let the allocated transmit power of user i be P_i (in W), which determines the transmission policy of the user. With the allocated bandwidth and optimized transmit power, the achievable transmission rate (in bits/s) is given by

$$r_i = k_i \cdot B_{min} \cdot log_2(1 + \frac{P_i g_i}{N_0 \cdot k_i \cdot B_{min}}), \tag{10}$$

where $g_i = h_i d_i^{-\alpha}$ is the channel gain between user i and the BS, h_i is the Rayleigh fading parameter, α is the path loss exponent, and d_i is the distance between user i and the BS.

Given sensing data size z_i, the transmission time at user i is

$$t_i^t = z_i/r_i, \tag{11}$$

and the transmission energy consumption E_i^t is thus given by

$$E_i^t = P_i \cdot t_i^t. \tag{12}$$

E. MCS Performance Metric

Similar to the work in [2], we use the utility of sensed data contributed by all the participants as our performance metric. A commonly-used logarithmic function $c_i \cdot log(1 + z_i)$ [2] is adopted to represent the utility of z_i-bit sensed data delivered by user i, where c_i is a weighting factor depending on the type of data. Due to the fact that more information-bearing data can contribute higher data utility, the utility function is monotonically increasing. Since a diminishing return is observed as the increase of data size (because of the repeated and redundant data), the utility function is modeled based on logarithmic function. Our objective function is thus given as

$$\max \quad \sum_{i=1}^{N} c_i \cdot log(1 + z_i). \tag{13}$$

III. Joint User Selection, Bandwidth Allocation, Sensing and Transmission

As user selection, bandwidth allocation, data sensing and transmission are closely coupled issues in MCS, we focus on jointly optimizing the aforementioned four policies under resource constraints in this section. Specifically, an optimization problem is formulated to jointly determine the user selection variable l_i, bandwidth allocation variable k_i, sensing data size z_i and transmit power P_i, as shown below.

$$\max_{l_i,k_i,z_i,P_i} \quad \sum_{i=1}^{N} c_i \cdot log(1 + z_i), \tag{14}$$

$$s.t. \quad \frac{z_i}{o_i} + \frac{z_i}{k_i B_{min} log_2(1 + \frac{P_i g_i}{N_0 k_i B_{min}})} \leq T, \ \forall i, \tag{14a}$$

$$e_i \cdot z_i + \frac{P_i \cdot z_i}{k_i B_{min} log_2(1 + \frac{P_i g_i}{N_0 k_i B_{min}})} \leq E_i, \ \forall i, \tag{14b}$$

$$\sum_{i=1}^{N} k_i B_{min} \leq B, \tag{14c}$$

$$l_i = \lceil k_i/B \rceil, \ \forall i \tag{14d}$$

$$0 \leq z_i \leq \lambda l_i, \ \forall i, \tag{14e}$$

$$0 \leq P_i \leq P_{max}, \ \forall i, \tag{14f}$$

$$l_i \in \{0,1\}, 0 \leq k_i \leq \lfloor B/B_{min} \rfloor, \ k_i \in \mathbb{Z}_0^+, \ \forall i. \tag{14g}$$

where (14a) and (14b) represent the time and energy constraints respectively. (14c), (14d) and (14g) are the user selection and bandwidth allocation constraints. (14e) indicates that the sensed data is valid only when the user is selected for the sensing task, and (14f) is the transmit power constraint.

From (14d), we notice that user selection variable l_i is only determined by bandwidth allocation variable k_i. As a result, we can simplify the problem in (14) by removing variable l_i. l_i is obtained when the optimal bandwidth allocation is found.

A. Optimal Transmit Power and Sensing Data Size

When a user is selected for the sensing task and allocated a certain amount of bandwidth for transmitting the sensed data, the optimal transmit power and sensing data size can be determined by the following proposition.

Proposition 1: Given the uplink bandwidth $k_i B_{min}$ allocated to user i, where $k_i > 0$ (or l_i =1), the optimal transmit power of user i is given by

$$P_i^*(k_i) = \begin{cases} P_{i,min}, & \text{if } \frac{E_i}{A_i(k_i,P_{i,min})} \leq \frac{T}{B_i(k_i,P_{i,min})} \\ P_{max}, & \text{if } \frac{E_i}{A_i(k_i,P_{max})} \geq \frac{T}{B_i(k_i,P_{max})} \\ P_{i,opt}, & \text{otherwise} \end{cases} \tag{15}$$

and the optimal sensing data size of user i is given by

$$z_i^*(k_i) = \begin{cases} \frac{E_i}{A_i(k_i,P_{i,min})}, & \text{if } \frac{E_i}{A_i(k_i,P_{i,min})} \leq \frac{T}{B_i(k_i,P_{i,min})} \\ \frac{T}{B_i(k_i,P_{max})}, & \text{if } \frac{E_i}{A_i(k_i,P_{max})} \geq \frac{T}{B_i(k_i,P_{max})} \\ \frac{E_i}{A_i(k_i b_i,P_{i,opt})}, & \text{otherwise} \end{cases} \tag{16}$$

where $A_i(k_i, P_i) = e_i + \frac{P_i}{k_i B_{min} log_2(1+\frac{P_i g_i}{N_0 k_i B_{min}})}$, $B_i(k_i, P_i) = \frac{1}{o_i} + \frac{1}{k_i B_{min} log_2(1+\frac{P_i g_i}{N_0 k_i B_{min}})}$, $P_{i,min} = \frac{10^{\frac{\mathrm{SNR_{min}}}{10}} \cdot k_i B_{min} N_0}{g_i}$, and $P_{i,opt}$ satisfies $\frac{E_i}{A_i(k_i, P_{i,opt})} = \frac{T}{B_i(k_i, P_{i,opt})}$.

Proof: Based on constraints (14a) and (14b), we get that

$$z_i \leq E_i / A_i(k_i, P_i), \tag{17}$$

$$z_i \leq T / B_i(k_i, P_i). \tag{18}$$

Since our objective is to maximize $\sum_{i=1}^{N} c_i \cdot log(1 + z_i)$, which is equivalent to maximizing the sensing data size z_i of each selected user i, the optimal sensing data size is thus given by

$$z_i^*(b_i) = \max_{P_i}(\min\{E_i/A_i(k_i, P_i), T/B_i(k_i, P_i)\}). \tag{19}$$

We first consider the first derivative of $A_i(k_i, P_i)$ with respect to P_i, which is given by

$$\frac{\partial A_i(k_i, P_i)}{\partial P_i} = \frac{\ln 2 \cdot \frac{k_i B_{min}}{1+x_i^n P_i}((1 + x_i^n P_i)\ln(1 + x_i^n P_i) - x_i^n P_i)}{(k_i B_{min} \ln(1 + x_i^n P_i))^2}, \tag{20}$$

where $x_i^n = g_i/(N_0 B^n)$. When $l_i = 1$, $0 < P_i \leq P_{max}$ must be guaranteed. As $(1 + x_i^n P_i)\ln(1 + x_i^n P_i) - x_i^n P_i$ is always positive when $P_i > 0$, we then get $\frac{\partial A_i(k_i,P_i)}{\partial P_i} > 0$. In other words, $A_i(k_i, P_i)$ is monotonically increasing with P_i. Since $B_i(k_i, P_i)$ is monotonically decreasing with P_i, $E_i/A_i(k_i, P_i)$ is then a monotonically decreasing function of P_i, and $T/B_i(k_i, P_i)$ is a monotonically increasing function of P_i.

To find the optimal transmit power that maximizes function $\min\{E_i/A_i(k_i, P_i), T/B_i(k_i, P_i)\}$, we first derive the feasible set of P_i. In practice, in order to successfully decode the received signal, the received signal-to-noise ratio $\mathrm{SNR} = 10 \cdot \log_{10}(P_i g_i/(N_0 B^n))$ (in dB) needs to be no smaller than a minimum value SNR_{min}. The minimum acceptable value of P_i is then obtained, or $P_{i,min} = \frac{10^{\frac{\mathrm{SNR}_{min}}{10}} \cdot \sum_{n=1}^{R} b_i^n N_0 B^n}{g_i}$

Since $P_i \in [P_{i,min}, P_{max}]$, we then get the maximum and minimum value of $E_i/A_i(k_i, P_i)$ with respect to P_i, i.e., $\max_{P_i}(E_i/A_i(k_i, P_i)) = E_i/A_i(k_i, P_{i,min})$ and $\min_{P_i}(E_i/A_i(k_i, P_i)) = E_i/A_i(k_i, P_{max})$. Similarly, the maximum and minimum value of $T/B_i(k_i, P_i)$ with respect to P_i are obtained, where $\max_{P_i}(T/B_i(k_i, P_i)) = T/B_i(k_i, P_{max})$ and $\min_{P_i}(T/B_i(k_i, P_i)) = T/B_i(k_i, P_{i,min})$

Case 1: $\max_{P_i}(E_i/A_i(k_i, P_i)) \leq \min_{P_i}(T/B_i(k_i, P_i))$

In this case, $E_i/A_i(k_i, P_i) \leq T/B_i(k_i, P_i)$ is always guaranteed for $P_i \in [P_{i,min}, P_{max}]$. As a result, $\min\{E_i/A_i(k_i, P_i), T/B_i(k_i, P_i)\} = E_i/A_i(k_i, P_i)$. We then get $z_i^*(k_i) = \max_{P_i}(E_i/A_i(k_i, P_i)) = E_i/A_i(k_i, P_{i,min})$, and $P_i^*(k_i) = P_{i,min}$

Case 2: $\min_{P_i}(E_i/A_i(k_i, P_i)) \geq \max_{P_i}(T/B_i(k_i, P_i))$

In this case, $E_i/A_i(k_i, P_i) \geq T/B_i(k_i, P_i)$ is always guaranteed for $P_i \in [P_{i,min}, P_{max}]$. Therefore, $\min\{E_i/A_i(k_i, P_i), T/B_i(k_i, P_i)\} = T/B_i(k_i, P_i)$, $z_i^*(k_i) = \max_{P_i}(T/B_i(k_i, P_i)) = T/B_i(k_i, P_{max})$, and $P_i^*(k_i) = P_{max}$.

Case 3: $\max_{P_i}(E_i/A_i(k_i, P_i)) > \min_{P_i}(T/B_i(k_i, P_i))$ and $\min_{P_i}(E_i/A_i(k_i, P_i)) < \max_{P_i}(T/B_i(k_i, P_i))$

Since $E_i/A_i(k_i, P_i)$ monotonically decreases with P_i, and $T/B_i(k_i, P_i)$ monotonically increases with P_i, then it is possible that $E_i/A_i(k_i, P_i) = T/B_i(k_i, P_i)$ when P_i increases from $P_{i,min}$ to P_{max} in this case. Therefore, $z_i^*(k_i) = E_i/A_i(k_i, P_{i,opt}) = T/B_i(k_i, P_{i,opt})$, where $P_{i,opt}$ satisfies the equality $E_i/A_i(k_i, P_{i,opt}) = T/B_i(k_i, P_{i,opt})$. ■

B. Optimal User Selection and Bandwidth Allocation

Based on Proposition 1, the optimization problem in (14) can be transformed as

$$\max_{k_i} \quad \sum_{i=1}^{N} c_i \cdot log(1 + z_i^*(k_i)), \tag{21}$$

$$s.t. \quad \sum_{i=1}^{N} k_i B_{min} \leq B, \tag{21a}$$

$$0 \leq k_i \leq \lfloor B/B_{min} \rfloor, \ k_i \in \mathbb{Z}_0^+, \ \forall i. \tag{21b}$$

where $z_i^*(k_i)$ is obtained based on Proposition 1 if $k_i > 0$; otherwise, $z_i^*(k_i) = 0$.

The optimization problem in (21) is to decide the number of bandwidth units (i.e., k_i) allocated to individual users such that the data utility contributed by all the users (or sum data utility) is maximized, where the total number of bandwidth units is $M = \lfloor B/B_{min} \rfloor$. To solve the problem, dynamic programming [10] is adopted. Specifically, we number the set of candidate users in the network as user $1, 2, \cdots, N$. Let s_i denote the number of bandwidth units allocated to the first i users in the network ($1 \leq i \leq N$), and k_i be the number of bandwidth units allocated to user i. We then have $s_{i-1} = s_i - k_i$. Let $f_i(s_i)$ denote the maximum sum data utility obtained when we allocate s_i bandwidth units to the first i users. We then have the following state transition equation:

$$\begin{cases} f_i(s_i) = \max\limits_{0 \leq k_i \leq s_i}(f_i(s_i), f_{i-1}(s_i - k_i) + \\ \qquad\qquad c_i \cdot log(1 + z_i^*(k_i))) \\ f_i(0) = 0 \end{cases} \tag{22}$$

With (22), the maximum sum data utility (or $f_N(\lfloor B/B_{min} \rfloor)$) as well as the optimal bandwidth units allocated to each user can then be calculated, as summarized in Algorithm 1, with computational complexity of $O(N \cdot M^2)$.

In conclusion, the optimal bandwidth allocation variable k_i is first obtained based on Algorithm 1, and then the optimal user selection is determined by $l_i = \lceil k_i/B \rceil$. The optimal transmit power and sensing data size of each selected user are then determined by Proposition 1. Thus far, the optimal joint sensing and communication scheme is obtained.

Algorithm 1 Optimal Bandwidth Allocation

```
Input: B, B_min
M = ⌊B/B_min⌋   /*the total number of bandwidth units*/
f, p, c = [[0 for i = 0 : M] for j = 0 : N]
U = [0 for i = 1 : N]
for i = 1 : N do
  for j = 1 : M do
    P, z = Proposition 1(j)
    c[i][j] = c_i · log(1 + z)
for i = 1 : N do
  for j = 1 : M do
    num = 0
    for k = 0 : j do
      if f[i][j] < f[i − 1][j − k] + c[i][k]
        f[i][j] = f[i − 1][j − k] + c[i][k]; num = k
    p[i][j] = num
s = p[N][M]   /*bandwidth units allocated to the last user*/
r = M − s   /*remaining bandwidth units*/
for i = N : −1 : 1 do
  U[i] = s; s = p[i − 1][r]; r− = s
return U   /*return the allocated result of each user*/
```

IV. Simulation Results

In this section, the effectiveness of our proposed framework is evaluated through experimental simulations on a typical computer with 3.2 GHz Intel CPU 6500.

A. System Parameters

We consider an MCS system consisting of one agent-deployed BS and N mobile users, where N ranges from 20 to 200. The parameters used in the MCS system are listed in Table I. Since there are few existing works concentrating on joint design of sensing and communication in a resource constrained MCS, we consider the following four baseline policies as comparison references. The first one is *random user selection* (RUS) policy, which jointly optimizes the bandwidth allocation, sensing data size and transmit power given the user selection policy. The second one is *random bandwidth allocation* (RBA) policy that randomly determines user selection and bandwidth allocation, while optimizing the sensing data size and transmit power (similar to that in [2]). The third one is *fixed sensing duration* (FSD) policy which allocates fixed time duration (e.g., half of T) for data sensing. The last one is *random transmit power* (RTP) policy where each selected user chooses a random transmit power for data transmission.

B. Performance Comparison

Fig. 2 illustrates the total data utility obtained versus the total number of users under different policies with T = 10s. We can see that the data utility obtained always increases with the total number of users (except for RBA policy). This is because more mobile users in the network indicates that more users can be selected for the sensing task if the wireless bandwidth is adequate, and more mobile users also increases the chance of having higher data utility contributed by new users, resulting in an increased sum data utility. We also find that our proposed policy provides the best performance, followed by RTP, FSD, RUS and RBA policies. RBA policy provides the worst performance as it not only determines the set of users for the task randomly, but also allocates the bandwidth to the set of selected users randomly.

TABLE I
MCS SYSTEM PARAMETERS

Notation	Description	Value
N	# of mobile users	20-200
P_{max}	Maximum transmit power	23 dBm [9]
E_i	Energy of user u_i	0.01-0.1 J [2]
T	Sensing task's time requirement	1-10 s
B	Total wireless bandwidth	20 MHz [8]
B_{min}	Minimum bandwidth unit	200 KHz
d_i	Distance between BS and user i	10-200 m
o_i	Sensing data rate of user i	$10^5 - 10^6$ bits/s [2]
e_i	Sensing energy consumption per bit	$10^{-12} - 10^{-11}$ J/bit [2]
N_0	Noise power density	-174 dBm/Hz [8]

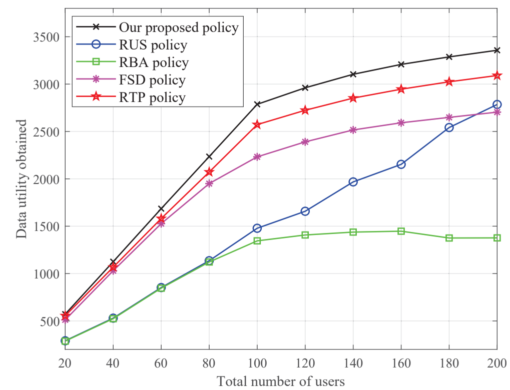

Fig. 2. Data utility obtained vs. total number of users

Fig. 3 shows how the total data utility obtained changes with the available bandwidth B. We set $T = 10s$, $N = 120$ and $E_{max} = 0.1J$ in Fig. 3. We can observe that the data utility increases with B. This is because more available bandwidth in the network can always lead to more users being selected for the sensing task and/or an increased amount of bandwidth

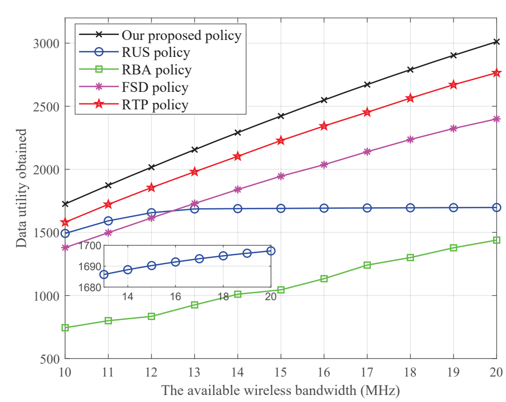

Fig. 3. Data utility obtained vs. the available wireless bandwidth

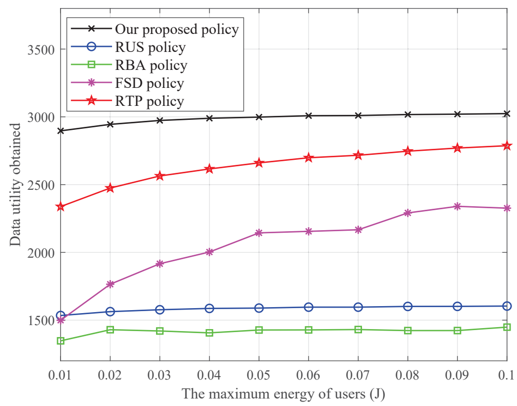

Fig. 4. Data utility obtained vs. the maximum energy of users

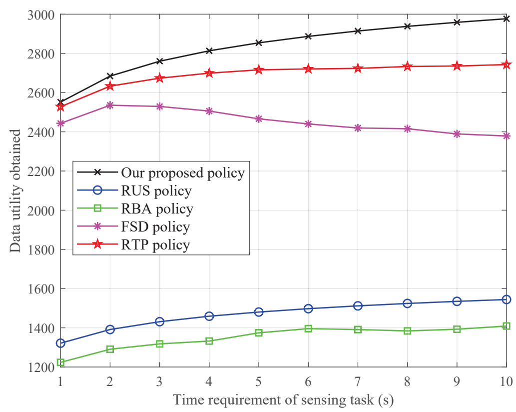

Fig. 5. Data utility obtained vs. sensing task's time requirement

allocated to the selected user. The improvement of RUS policy is small because we fix the set of (randomly) selected users in Fig. 3 when the available bandwidth varies. As a result, although more available bandwidth can increase the amount of bandwidth allocated to the user and increase the amount of data sensed by the user, the improvement on data utility can be small due to the repeated and redundant data sensed by the same user.

In Fig. 4, the total data utility obtained is shown versus the maximum energy of users (denoted as E_{max}) with $T = 10s$ and $N = 120$. E_{max} varies from 0.01J to 0.1J, and the energy of each user (E_i) is uniformly distributed in the range $[E_{max}/10, E_{max}]$. Again, we can see that the proposed policy provides the best performance. In particular, our proposed policy provides performance gain of about 14%, 47%, 88% and 111% as compared with RTP, FSD, RUS and RBA policies, respectively. We also find that the data utility increases with the maximum energy of users, but the improvement is small under our proposed policy, RUS and RBA policies. This is because although the increase of energy can lead to an increased amount of sensed data, the improvement on data utility can be small when the amount of data sensed is large enough.

In Fig. 5, the total data utility obtained is illustrated versus task requirement T with $N = 120$. We can see that the data utility increases with T for all policies except for FSD policy. This is because the sensing duration of FSD is fixed to half of T. The energy consumption for sensing under FSD policy is thus increased with T. Since the available energy of each user is fixed in Fig. 5, the energy allocated for data transmission is then reduced, resulting in a reduced data utility for FSD policy. We further find that the performance gap between our proposed policy and RTP policy increases with T. This is because RTP policy determines the transmit power of each user randomly, resulting in a non-optimal energy allocation for data transmission. As a result, when the available energy of user is insufficient, or the sensing time requirement T is large, the performance gap due to such a non-optimal energy allocation becomes non-negligible.

V. CONCLUSION

In this paper, we have designed a joint sensing and communication framework over resource constrained MCS systems. An optimization problem is formulated and solved to jointly perform the user selection, bandwidth allocation, data sensing and transmission involved in the system, with the aim of maximizing the performance of sensing task. Numerical results show that our proposed policy can achieve up to 14%, 47%, 88% and 111% performance improvement as compared with four baseline policies, i.e., RTP, FSD, RUS and RBA policies.

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