Novel Task Allocation Method for Emergency Events under Delay-Cost Tradeoff

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***Abstract*—With the emergence of three new paradigms, namely the Internet of Things (IoT), cloud/edge computing and mobile social networks; Mobile Crowd Sensing (MCS) has emerged as a potential approach for data collecting in numerous applications, such as traffic management, infotainment, disaster management or public safety. MCS mechanisms are receiving a lot of attention, both from research and development areas, showing their impact and benefit. But their optimization is still under development, mainly due to the large number of involved parameters. A major field within MCS relates to crowd management for emergency situations, where the management and optimization mechanisms become crucial to local authorities. To tackle this problem, in this work, we propose an MCS hybrid worker selection scheme that operated various modes depending on the delay-cost requirements. Our scheme exploits the user behavior to achieve an optimal bi-objective for any delay-cost requirement. We use simulations to evaluate the performance of our proposal, and we show the optimal and different sub-optimal solutions that can match the delay-cost requirements.**

***Index Terms*—MCS; Hybrid System; Task Allocation; Crowd Management; Sub-Optimal.**

I. Introduction

With the increased growth in smart mobile devices and wearables that carry an arsenal of embedded sensors, Mobile Crowd Sensing (MCS) has been a rising technique in collecting large amounts of data through these devices [1]. The ubiquity and pervasiveness of such devices, as well as their expanded short-range and long-range communication capabilities and networking interfaces, amplify MCS's ability to improve the perception of the surrounding environment. The adoption of mega-scale MCS allows for real-time and dynamic data gathering from multiple points of interest through mobile devices. In MCS, task allocation and sensing cost are key issues for MCS campaign managers that may have an impact on the quality of system performance [2].

The research in [3] looked at the issue of task assignment and user path planning, with the goal of reducing overall task latency while simultaneously focusing on a high number of completed MCS tasks. However, most systems primarily focus on task completion as an objective, and do not take user preferences into consideration when assigning tasks. As a result, they may leave users unhappy and have an impact on future user involvement. This led to other systems in [4] to focus on user satisfaction and user preference as their metric [5] in the system performance and suggested a personalized task assignment method that takes into account worker scheduling and respects user's preferences.

In addition, other works [6] have focused on creating novel budget-constrained task assignment algorithms through reputation-aware auctioning, where historical user behavior is collected to rate their performance and match their future tasks accordingly. Reputation aware personalized task recommendation have gained attention [7] [8] as such systems increase the overall Quality of Service (QoS), while selecting quality data from selected users. QoS can be represented through several metrics as minimum rate or maximum delay among others. Within this work, emergency events are considered, thus delay will be the system QoS indicator.

Moreover, several trajectory prediction algorithms [9] [10] have been suggested and shown to be successful to some extent, dealing with the challenge of unexpected real-life situations in MCS. As a result, the final sensing quality for some activities may be poorer than anticipated. Therefore, intelligent neural networks that focuses on predicting user's movement patterns [11] are studied to particularly optimize the time spent in a sensing zone, and therefore to effectively predict future movement patterns. The main purpose of such prediction algorithms is to improve the overall task completion ratio of the system, by exploiting the opportunistic worker that is more predictable, and hence more useful by the system.

Clearly, there are significant challenges in collecting data from the end-user in such a way that trade-offs between the user gains and the campaign managers costs are maintained. To deal with this problem, we take the position that MCS encompasses a broad range of user participation, with participatory sensing and opportunistic sensing at opposite extremes of the spectrum [12]. We propose to exploit the user's diversity and propose a hybrid worker selection method based on four distinct user types.

Traditionally, two modes of operation in a MCS campaign are considered: participatory sensing (where users are required to travel to specific locations to complete tasks) and opportunistic sensing (where the tasks are completed autonomously without the intervention of the user). However, as we tackle the cost in our system optimization, then another differentiation is needed among users: whether they can directly upload the sensed data, and we denote them as participatory uploading, or they wait until they can have access to cheaper technology (e.g., free WiFi) to upload their data, for what we name them as opportunistic uploading. Our target is to optimize the system performance in terms of QoS-delay and cost, and therefore the combinations of all users must be considered, thus four different kinds of participants are available in the scenario. For emergency situations, delay requirements are critical and must be satisfied.

Due to a significant challenge in collecting data from the end-user and uploading it under a time constraint, this work will focus on finding the optimal minimum cost to acquire information under a specific delay requirement by presenting a worker selection method based on the four different participant's modes. The worker selection method will take into account the user's choice for involvement, making maximum use of the already existing human sensing resources, since users preferred modes of sensing in real-life situations are not all identical. There will exist a portion of people who might be unwilling to participate in data uploading as their mobile data plan is limited or they use it very sparsely but might be willing to travel to various locations to collect data. On the other hand, there will be users who decide to participate in uploading the data as needed, but without asking them to move from their location to complete the task. For these reasons, the proposed system takes into consideration all possible user preferences to maximize user involvement, ultimately leading to higher task completion ratio.

Moreover, the proposed hybrid worker selection method is highly advantageous to task managers as it creates a dynamic system. Such a method will allow the system to run under different modes of operation depending on the delay constraint requirement while keeping the budget limit in mind. For example, for an emergency event, the system operator will be able to allocate the task to users with participatory nature, at the extent of higher cost; while if the task is delay tolerant, other kinds of users can be selected to decrease the budget.

The rest of the work is organized as follows. In Section II, we review related previous work. In Section III, we introduce the system model and the MCS scheme, followed by Section IV, where simulations are used to assess the performance of the suggested scheme. Finally in Section V, the paper conclusions are provided.

II. Related Work

In the literature, the difficulty of identifying an abnormal change in a monitored sensory variable that is suggestive of an emergency scenario is examined in [13] . The researchers in [14] looked at employing sensor-enhanced smart gadgets to identify a shift in some visible phenomena that might signify an oncoming or ongoing emergency scenario. On the other hand, a greedy user reputation aware algorithm that tries to strike a balance between decision time and ultimate decision quality was discussed in [15], with comprehensive simulations to show how this strategy improves the proper detection rate over a reputation unaware baseline.

One of the major disadvantages of crowd sensing, however, is the lack of control over the geographical distribution of edge sensor nodes [16]. The density of the sensory network is directly connected with the population density since the edge sensor nodes, or smart devices, are carried by the participants. Because of the crowd sensing members' daily activities, such as leaving for work in the morning and returning home at night, the population density and geographic density of the sensor network change over time. The researchers in [17] present a location and time aware multitask allocation algorithm that allows users to select between several sensing tasks while keeping in mind the time constraints, along with a budget mechanism that is utilized to estimate the budget for each activity and the task requirements. Similarly, [18] presents a customized task allocation technique for reducing total cost, in which the cost for a user to complete a job is determined by both total movement distance and the task selected by the user.

For this reason, our proposal of a hybrid user/task allocation method tackles the problem of unbalanced sensor network distribution, since it allows for gaining control over the users trajectory paths when necessary; allowing crowd sensing managers to take advantage through controlling the density of the sensor network to a geographical spot, where information gathering for an emergency is needed immediately.

There have been several previous works [19] [20] [21] that tackled the idea of hybridization in various ways. In [19] the authors present a hybrid task allocation framework that blends the opportunistic mode and the participatory mode via a two-phased architecture, an online phase where participatory users operate and an offline mode where opportunistic users operate. During the offline phase, a group of individuals is hired as opportunistic workers to execute sensing tasks while on their regular routes. During the online phase, some participatory workers are sent to regions where opportunistic workers are unable to fulfill tasks. The opportunistic workers are given a fixed amount of reward during the sensing period from the total budget, and the remainder of the budget is spent on the online phase (where only participatory workers operate). This type of system generally operates opportunistically or participatory in terms of time and makes use of participatory workers only to finish what is left behind from the opportunistic offline phase.

Participatory sensing is preferred to opportunistic sensing for time-sensitive activities, like emergency situations [20]. This is because workers in participatory sensing may walk to task sites on purpose and complete the sensing and uploading operations on time, resulting in a higher coverage and task completion ratio. However, incentives for participatory sensing are more expensive since MCS workers are more inclined to travel and submit data samples only if they are given a significant incentive. The authors in [21] have focused on the link between the number of active participants and the number of tasks to be performed. Multi-task allocation algorithms for bi-objective goals have been proposed depending on the number of workers and tasks available, in order to minimize the total distance under a specific budget constraint.

III. MCS Scheme for Delay Critical Applications

A. System Model

We will define participatory uploading as users who not only participate in sensing the task, but actively upload the sensed data in a participatory fashion (i.e using mobile data instead of waiting for Wi-Fi connection). On the other hand, opportunistic uploading will then be users who wait until they are connected to the internet for data uploading, resulting in having a higher average delay time.

These two different modes of operation can be viewed as opposites in terms of latency and cost. It is clear that participatory sensing/uploading PP type of users will have the least amount of average delay between task assignment and task completion (data uploading), and the opportunistic sensing/uploading OO will have the most amount of delay. However, PP users will require a higher incentive to complete tasks compared to OO users, since these types of user will be continuously moving out of their route to complete the tasks, and they will be using their personal mobile data to upload the sensed information. Therefore, we reached a delay-cost trade-off, where the cost will be the amount of incentive required for each user type to complete a task, which will be different for each user depending on their delay time.

In addition to these two user types, there will exist two more types of users which will be participatory in sensing but opportunistic in uploading PO and opportunistic in sensing/participatory in uploading OP. There is no certain way to know which of these two types of users provides less amount of delay, we will assume in this work however that PO is faster than OP in terms of task completion since these users actively participate in tasks by going to task locations.

B. Hybrid User/Task Allocation

The objective of the system is to find an optimal point for a delay-cost problem where the four proposed user types PP, PO, OP and OO will be used to find the optimal balance at any given required delay threshold D_{th}. The four user types PP, PO, OP and OO will have a corresponding average delay times d_{pp}, d_{po}, d_{op} and d_{oo} and budget cuts from the total budget b_{pp}, b_{po}, b_{op} and b_{oo} respectively. For simplicity, we assume that any d delay includes the time required to upload the data as well as the time required to acquire the data from a specific location, meaning that the delay times are assumed to be the total average time required for a user to complete a task from task assignment to data uploading.

We arrive at the following minimization problem to model the system

$$\begin{aligned} &min\ b_{pp}PP + b_{po}PO + b_{op}OP + b_{oo}OO \\ &\quad s.t.\ PP + PO + OP + OO = 1 \\ &\qquad\quad d_{pp}PP + d_{po}PO + d_{op}OP + d_{oo}OO \leq D_{th} \end{aligned} \tag{1}$$

where the constants have been assumed with the following order

$$b_{pp} > b_{po} > b_{op} > b_{oo}$$

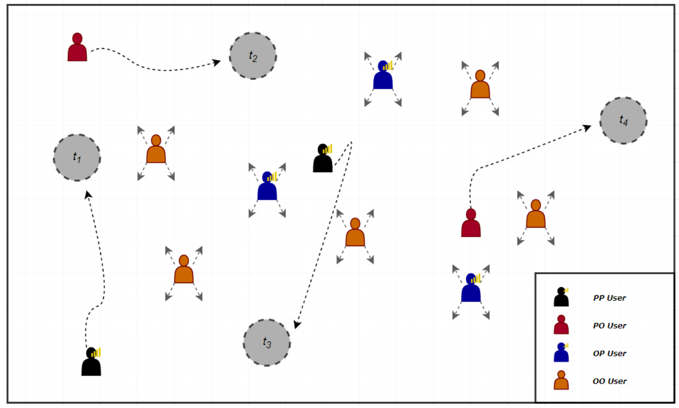

Fig. 1. System model with the four proposed user types

and

$$d_{pp} < d_{po} < d_{op} < d_{oo}$$

The optimization problem can be reformulated in a more tractable way as

$$\begin{aligned} &min\ \ f(x) = \sum_{i=1}^{N} b_i x_i \\ &s.t.\ c_1(x) = \sum_{i=1}^{N} x_i - 1 \\ &\quad c_2(x,s) = \sum_{i=1}^{N} d_i x_i - D_{th} + s^2 \end{aligned} \tag{2}$$

Here s is a slack variable to turn the inequality equation into an equivalent equation. We have the following equations. The Lagrangian equation will be formulated thus as

$$L(x,\lambda,\mu,s) = f(x) + \lambda c_1(x) + \mu c_2(x,s) \tag{3}$$

$$\nabla L = \begin{cases} b_j x_j + \lambda x_j + \mu d_j x_j = 0, \quad j = 1,\cdots,4 \\ \sum_{i=1}^{N} x_i - 1 = 0 \\ \sum_{i=1}^{N} d_i x_i - D_{th} + s^2 = 0 \\ \mu s = 0 \end{cases}$$

Taking the partial derivative for each equation with respect to x_j, λ and μ.

$$\frac{\delta L}{\delta x_j} = 2b_j x_j + 2\lambda x_j + 2\mu x_j b_j \quad j = 1,\cdots,4 \tag{4}$$

$$\frac{\delta L}{\delta \lambda} = x_1 + x_2 + x_3 + x_4 - 1 \tag{5}$$

$$\frac{\delta L}{\delta \mu} = x_1 d_1 + x_2 d_2 + x_3 d_3 + x_4 d_4 - D_{th} + s^2 \tag{6}$$

There are two possible sets of solutions to the Lagrangian problem. The first is when $\mu = 0$, $s^2 > 0$. The other set of solutions is when $\mu > 0$, $s^2 = 0$. Notice that when the

Lagrangian multiplier μ is equal to zero, the delay constraint c_2 is inactive. Which leaves only the first constraint c_1 active. Therefore, the set of solutions that will result from this do not take into account the delay constraint, which is necessary in this problem. This means that the set of solutions when μ is equal to zero will not be part of the final solution.

From equation (5) we arrive at the solution where

$$f = b_j \ , \quad x_j = 1 \ , \quad \lambda = -b_j \ , \quad s^2 = D_{th} - d_j \ , \quad \mu = 0$$

$$j = 1, \cdots, 4$$

The other set of solutions is when $\mu > 0$, $s^2 = 0$. This set of solutions is when both constraints c_1 and c_2 are active. There are six possible conditions in this solution which are represented in the matrix below, as a result of having four user types since there are six different combinations between any two distinct user types. This is because D_{th} can only be in the range between two user type delay limits. As a result, if D_{th} is between d_1 and d_2, this will activate their respective user types x_1 and x_2, and assign the remaining user types to zero. The obtained general solution form states as

$$f(x) = b_i x_i + b_j x_j, \quad d_i \le D_{th} \le d_j \tag{7}$$

with the following parameters formulated as

$$x_i = \frac{d_j - D_{th}}{d_j - d_i}, x_j = \frac{d_i - D_{th}}{d_i - d_j}, \lambda = \frac{b_i d_j - b_j d_i}{d_i - d_j}, \mu = \frac{b_j - b_i}{d_i - d_j} \tag{8}$$

while the resultant budget is expressed as

$$b_i = \frac{1 - \frac{d_n^2}{\sum_{n=1}^{N} d_n^2}}{N - 1} \tag{9}$$

that considers N as the number of user's types. This budget division allows for a proportional increase of incentive to users who provide lower total delay times.

IV. Numerical Results

In this section, we present simulated results in order for the reader to realize the system performance, by changing several parameters in the scenario. The values for d_{pp}=20, d_{po}=60, d_{op}=80 and d_{oo}=120 minutes are assumed. Fig.2 clearly illustrates all possible solutions under a range of delay requirements spanning from d_1 up to and beyond d_4, thus covering emergency situations to delay-tolerant scenarios. The optimal solution is shown and how all other solutions compare to it. The two extreme cases of delay requirement equal to the thresholds are also shown as horizontal lines. All solutions are obviously between these two lines, as shown in the figure. Notice that all solutions start from the d_{pp} point, as before such a point even the user with the least delay will not be able to achieve the task delay requirement. Delay requirement larger than d_{oo} can be obviously achieved and with the least cost. Moreover, Fig.2 shows the performance of other sub-optimal solutions and compared to the optimal one, under different delay requirements.

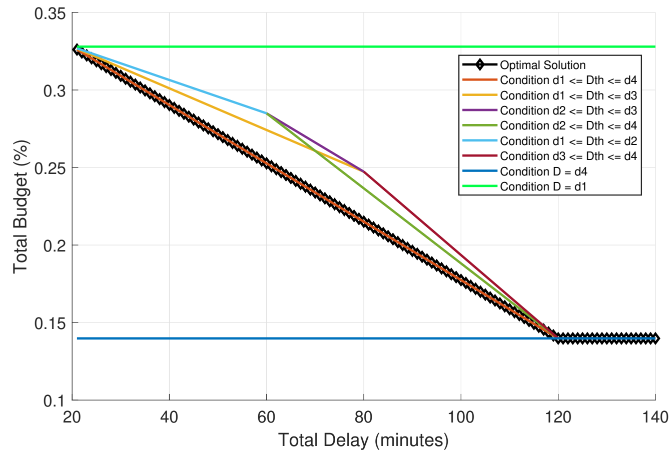

Fig. 2. All possible solutions under different delay threshold values

Such sub-optimal solutions represent alternatives for the manager to minimize the budget in any situation. For instance, if in any point there are no PP or OO users available and the delay requirement was 75 minutes, there would be 3 possible sub-optimal alternatives at that point. These alternatives are to combine users PO and OP with delays d_2 and d_3 (solution in purple), or to combine PP and OP with delay times d_1 and d_3 (solution in orange) which is less costly than the previous solution, or to combine PO and OO with corresponding delay times d_2 and d_4 (solution in green) which is the least costly but providing more delay than previous ones.

To highlight the achieved quality, Fig.3 shows the total quality achieved by the different types of solution. With the focus put on emergency applications, delay is assumed as the quality metric. Clearly, the solutions with more participatory users will achieve higher quality since they will be able to achieve lower delay times.

However, it is worth pointing out that the selection from all user types achieves higher quality in comparison with three solutions, namely the solution that runs PO and OP, the solution that runs OP and OO and finally the purely opportunistic OO only solution.

f	PP	PO	OP	OO	λ	μ	s^2	CONDITION
b_1	1	0	0	0	$-b_1$	0	$D_{th} - d_1$	$D_{th} \ge d_1$
b_2	0	1	0	0	$-b_2$	0	$D_{th} - d_2$	$D_{th} \ge d_2$
b_3	0	0	1	0	$-b_3$	0	$D_{th} - d_3$	$D_{th} \ge d_3$
b_4	0	0	0	1	$-b_4$	0	$D_{th} - d_4$	$D_{th} \ge d_4$
$\frac{b_4(d_1-D_{th})}{d_1-d_4} + \frac{b_1(d_4-D_{th})}{d_4-d_1}$	$\frac{d_4-D_{th}}{d_4-d_1}$	0	0	$\frac{d_1-D_{th}}{d_1-d_4}$	$\frac{b_1d_4-b_4d_1}{d_1-d_4}$	$\frac{b_4-b_1}{d_1-d_4}$	0	$d_1 \le D_{th} \le d_4$
$\frac{b_4(d_2-D_{th})}{d_2-d_4} + \frac{b_2(d_4-D_{th})}{d_4-d_2}$	0	$\frac{d_4-D_{th}}{d_4-d_2}$	0	$\frac{d_2-D_{th}}{d_2-d_4}$	$\frac{b_2d_4-b_4d_2}{d_2-d_4}$	$\frac{b_4-b_2}{d_2-d_4}$	0	$d_2 \le D_{th} \le d_4$
$\frac{b_4(d_3-D_{th})}{d_3-d_4} + \frac{b_3(d_4-D_{th})}{d_4-d_3}$	0	0	$\frac{d_4-D_{th}}{d_4-d_3}$	$\frac{d_3-D_{th}}{d_3-d_4}$	$\frac{b_3d_4-b_4d_3}{d_3-d_4}$	$\frac{b_4-b_3}{d_3-d_4}$	0	$d_3 \le D_{th} \le d_4$
$\frac{b_3(d_2-D_{th})}{d_2-d_3} + \frac{b_2(d_3-D_{th})}{d_3-d_2}$	0	$\frac{d_3-D_{th}}{d_3-d_2}$	$\frac{d_2-D_{th}}{d_2-d_3}$	0	$\frac{b_2d_3-b_3d_2}{d_2-d_3}$	$\frac{b_3-b_2}{d_2-d_3}$	0	$d_2 \le D_{th} \le d_3$
$\frac{b_3(d_1-D_{th})}{d_1-d_3} + \frac{b_1(d_3-D_{th})}{d_3-d_1}$	$\frac{d_3-D_{th}}{d_3-d_1}$	0	$\frac{d_1-D_{th}}{d_1-d_3}$	0	$\frac{b_1d_3-b_3d_1}{d_1-d_3}$	$\frac{b_3-b_1}{d_1-d_3}$	0	$d_1 \le D_{th} \le d_3$
$\frac{b_2(d_1-D_{th})}{d_1-d_2} + \frac{b_1(d_2-D_{th})}{d_2-d_1}$	$\frac{d_2-D_{th}}{d_2-d_1}$	$\frac{d_1-D_{th}}{d_1-d_2}$	0	0	$\frac{b_1d_2-b_2d_1}{d_1-d_2}$	$\frac{b_2-b_1}{d_1-d_2}$	0	$d_1 \le D_{th} \le d_2$

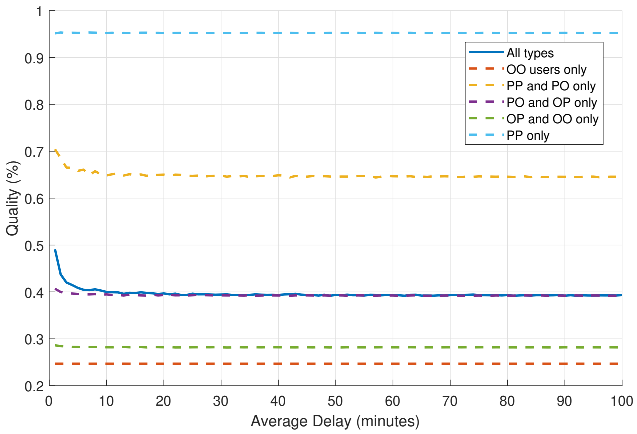

Fig. 3. Quality of solutions under different budget values

V. Conclusions

In this work, we study the task assignment problem in mobile crowd sensing for emergency applications. To address this issue, we offer a hybrid user selection system for MCS that allows for several operating modes based on the delay-cost needs by leveraging user behavior through categorization to reach an optimum bi-objective for any delay-cost requirement. We examine the performance of our approach using simulations, and we show that merging two different user types results in various sub-optimal solutions along with an optimal solution for different minimum delay-cost points.

Through simulations, we have proven that the proposed system allows for various sub-optimal paths. Therefore, such a system is highly flexible and realistic when put into a real-world application since it does not only work for one specific solution, but rather a span of solutions the cost under any given delay constraint. Such flexibility for the system allows for a wide range of applications through dynamic user type selection, which opens the door for emergency usage (selecting a lower delay threshold) and non-emergency usage (selecting a higher delay threshold). Since the value of the delay threshold controls the movement from these two opposite ends, further improvements can be made towards working on a smart and predictive mechanism for selecting the required delay threshold for any situation.

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