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An Incentive Mechanism for UAVs Crowdsensing Markets, a Negotiation Approach

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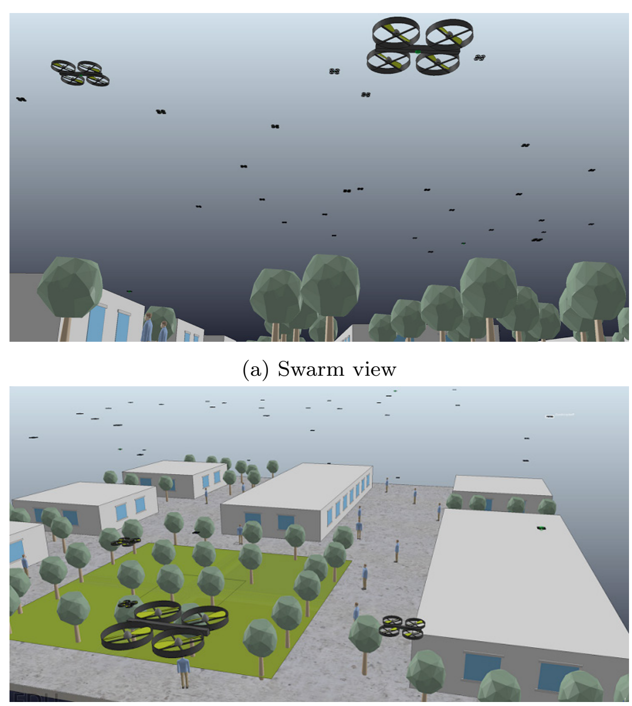
Abstract: In this paper, we present an incentive mechanism for Unmanned Aerial vehicles (UAVs) crowdsensing. In particular, we propose a solution to the problem of sensing coverage of lower regions of the atmosphere where a set of UAVs transverse it as part of their daily activities. We propose a UAV sensing market where data collection is an additional by-product that UAVs obtained while following their regular trajectories. In this model, participants use negotiation to compete and cooperate with each other while participating in data collection campaigns. Using the Virtual Robotics Environment (VRep) and extensive simulations, we show that our algorithm performs well in terms of sensing coverage, and participants retention while using a limited budget.

Keywords: Cost Oriented Automation, Intelligent Systems and Applications, Artificial intelligence and Applications, Deep Learning.

1. INTRODUCTION

Swarm Robotics is an area of the Multi-Robot System where large groups of robots come together to jointly develop complex tasks. Usually, the tasks that are developed by a swarm of robots are not possible to develop by an individual robot. The idea of a robot swarm is inspired by animals that present complex social behaviors such as bees, pigeons, fish, horses, ants, wolves among many others. Collective behavior generates great advantages for each of the individuals, for example, in the case of the school of fish where each of the individuals protects itself from predators by joining the school Rossi et al. (2018). Here, each individual develops coordinated movements that prevent the predator to catch the prey. In the same way as animals, robot swarms help robots to perform tasks that are individually difficult or impossible to perform such as last-mile package transport, surveillance, exploration of dangerous areas for humans, search and rescue of victims in disaster areasCardona and Calderon (2019), León et al. (2016), Cardona et al. (2021), and remote sensing (Jaimes and Calderon, 2020; Modali et al., 2020), (Jaimes and Calderon, 2018) among many others.

In the last decades, research and development around the area of Unmanned Aerial Vehicles have grown spectacularly. This development brings us closer to the idea of having multi-robot systems based on drones and consequently in the very near future to be able to develop robot swarms based on UAVs. These developments will allow the implementation of applications and the execution of missions reserved for UAV Swarms as mentioned previously. At the same time that a swarm develops its primary task, it is possible to perform remote sensing tasks



(a) Swarm view

(b) Swarm top view

Fig. 1. Swarm deployment on residential area

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without affecting the development of the original mission. This type of secondary application is called Crowd Sensing due to the large number of agents involved in the swarm robot. Figure 1 shows a swarm deployment on a residential region.

This paper presents the concept of performing crowdsensing as a secondary application in terms of optimizing the cost of the remote sensing mission. We propose a cost-oriented crowdsensing mission in terms to minimize the sensor sample collection through the take vantage of the primary missions in a UAV's swarm.

In this paper, we propose an incentive mechanism in the context of UAV Swarm. In these settings, a set of sensing tasks located at the lower regions of the atmosphere are posted by a crowdsourcer or data buyer. Given the large number of agents that compose a swarm, there is a high probability that some of the sensing tasks will be located in the trajectories and sensing range of some swarm members. An appealing characteristic of this approach is that UAVs don't have to interrupt their activities or deviate from their trajectories to participate in the sensing campaign. In addition, unlike most crowdsensing systems, the proposed mechanism allows participants to collaborate with each other by using a set of negotiation algorithms.

2. LITERATURE REVIEW

In the last few decades, research and development around swarm robotics have increased exponentially. Swarm robotics is inspired by the behavior of social animals such as birds, ants, bees, and fish. These species are the greatest example of how the simple behaviors of an individual can generate complex behaviors when they interact in society. Swarm robotics is based on the swarm intelligence theory to be able to create groups of robots that interact generating behaviors with characteristics of robustness, scalability, and flexibility. Swarm robotics has shown a very promising area of research where the applications on this theory can be used in many potential application fields such as precision agriculture, military robots and autonomous army, nano and micro-robotics, search and rescue of victims in disaster areas, remote sensing, mobility, and transportation, last-mile delivery among many others.

In recent years the study and research of swarm robotics have focused on the development of different behaviors such as aggregation, pattern formation, collective exploration, self-assembly, coordinated movement, and task assignment are some of the most important research areas. As mentioned above, the development of AUVs has increased in recent years, and in this way, the possibility of having swarms of AUVs also increases. In the same way that Swarm technology has grown, so has wireless communication, providing solutions based on crowdsensing which has attracted the industry due to the amount of data that can be collected. Most of the data that is collected in Crowdsensing comes from the use of cell phones and smart vehicles, but with the advent of Swarm AUVs, data collection could change dramatically.

Swarm robotics is composed of crowds of UAVs, this opens the door for a multitude of crowdsensing applications where the participants don't have many limitations in terms of mobility. Applications such Motlagh et al. (2017) the authors propose a surveillance system based on a UAV network. Following a similar approach, the work in Bacco et al. (2017) propose another surveillance system, but this time base on the use of the UAV's cameras to do face recognition. Other works using crowdsensing use swarm technology to provide internet services in areas of natural disasters Erdelj et al. (2017)

Unlike most traditional swarm applications which are usually designed to perform specific missions, our approach doesn't disturb the daily activities of participants. Here, the sensing task is a by-product that may supplement the income generated by participants in their primary activities.

3. SYSTEM MODEL

This section describes the different elements of the proposed incentive mechanism for UAVs crowdsensing and how these elements work together to incentivize UAVs participants to collect sensing samples. Elements of the mechanism include a set participant (UAVs), a platform or data buyer, a mechanism for recurrent data acquisition, a geometric model for covering a target space, and a set of negotiation algorithms that allow collaboration among participants. In this setting, a platform broadcasts its intention of buying data samples from some specific locations of the space. Responding to this request UAVs within a close distance to the Places of Sensing Interest (PsI) will submit a bid for the completion of the sensing task. The platform will collect the bids submitted by all the interested participants, at all the different PsIs, and then it will select the winner's bids based on a particular rule. The winners are notified by the platform, and these participants use their onboard sensors to collect sensing samples and send them to the platform. The platform receives the samples and send back payments to the winners. This close a round of a recurrent reverse auction. This process is repeated at regular time intervals over and over.

3.1 Crowdsourcer

The crowdsourcer or data buyer is a cloud-based application in charge of posting sensing tasks, and data acquisition. The goal of crowdsourcer is to acquire a representative set of samples in order to re-construct a variable of interest within a limited budget. In other words, the goal is to maximize coverage while minimizing cost. To meet these two objectives the crowdsourcer combine the use of a recurrent reverse action to obtain a set of bids from the interested participants, and an optimization algorithm to acquire the bids that maximize coverage while minimizing cost. We use the Auction Dynamic Price with Virtual Participation Credit and Re-recruitment (RADP-VPC-RC) Lee and Hoh (2010) to obtain a set of bids, and the greedy budgeted maximum coverage algorithm Khuller et al. (1999) to select the winners. The GIA incentive mechanism proposed by Jaimes Jaimes et al. (2012) combines these two elements, and it is the data acquisition framework used in this paper

Figure 2 illustrates how the acquisition data approach works. In this example, a crowdsourcer uses a reverse

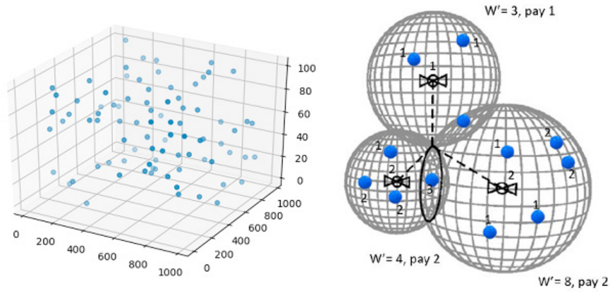
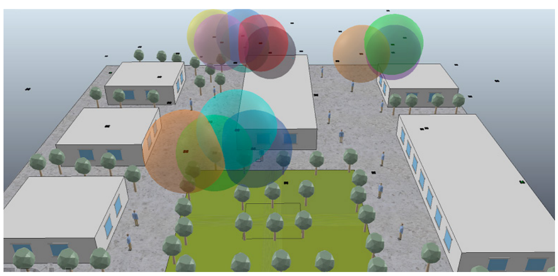
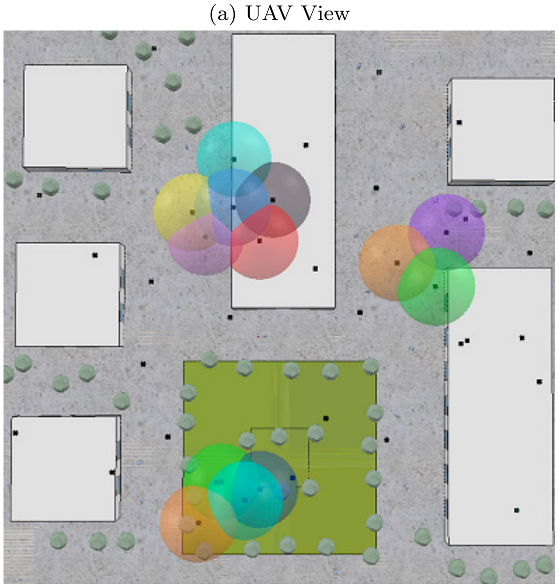


Fig. 2. AUVs participants

auction to advertise three PsI or sensing tasks. Then, the interested AUVs in the vicinity of the PsIs show their interest by submitting their bids. The crowdsourcer uses the greedy budgeted coverage algorithm to select the winners. A winner sample i is the one that maximizes the ratio $\frac{W'_i}{c_i}$, where W'_i is the number of samples in the sensing range of i (samples within the sphere centered at i) and c_i is the bid price of the winner sample i.



(a) UAV View

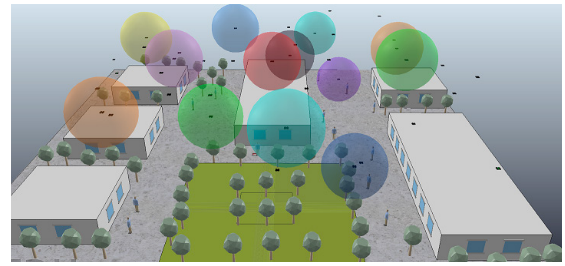


(b) Top View

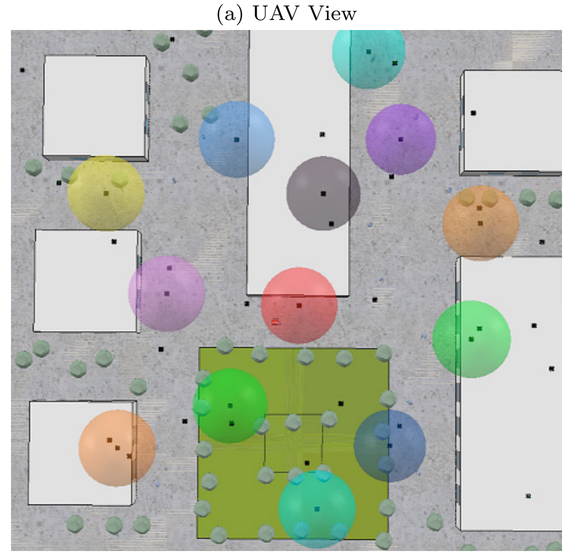
Fig. 3. three cluster of redundant samples

Thus, once a sample i is acquired, no samples in the sensing range of i are acquired to avoid data redundancy. Figure 3 shows the effect using a sample acquisition rule based only on the bid price. Thus, the cheapest samples may be clustered, resulting in the acquisition of a redundant set of samples that don't represent the variable of interest.

In contrast, Figure 4 shows the case, when the crowdsourcer uses the budget maximum coverage algorithm as a rule for data acquisition. In this case, the crowdsourcer may be not able to acquire the same number of samples than when the acquisition is based only on bid price. However, the acquired samples are better distributed and correspond to a representative set of the variable of interest.



(a) UAV View



(b) Top View

Fig. 4. Acquiring a set of representative samples

3.2 Participants

Figure 5 corresponds to a simulation that shows a set of UAVs taking off and landing at different locations and reaching different altitudes. They represent participants picking up and delivering goods on regular basis. We consider these participants a set of rational players, who are attracted by the rewards offered by the platform who are willing to participate if they are sufficiently incentivized. Thus, we consider them selfish and always willing to maximize their utility. In particular, they are a set of UAVs with onboard sensors traversing the 3D space while carried out activities such as picking up and delivering as part of a logistic chain.

3.3 Recurrent Cooperative Incentive Mechanism (RCIM)

This section describes the strategy adopted by participants as a response to the platform acquisition mechanism. In this setting, the platform advertises the set o $PsIs$ and acquires a subset of sensing samples following the approach described in Section 3.2. However, after the first round participants start to behave in their self-interest. This behavior takes the form of negotiation algorithms.

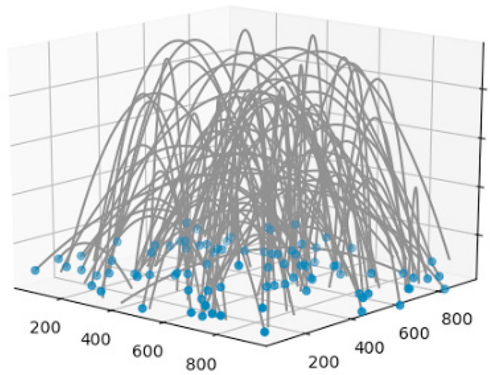


Fig. 5. A set of UAVs trajectories

In which, the winners (those who sold their sample in the current round) propose a deal to the losers (those who were not able to sell their samples), and the losers evaluate the convenience of accepting or rejecting the proposed deal. Thus, this approach includes three different steps: Neighbors' Discovery, Dealer Decision Algorithm (DDA), Dealer negotiation algorithm (DNA), and Dealer neighbor negotiation algorithm(DNNA).

Neighbors's Discovery Here, A disk of radius R (participant radius of sensing) is drawn on every AUV location, and an edge from the disk center AUV_k to any other AUV_j is drawn when $d(AUV_k, AUV_j) \leq R$. The output of the neighbor's discovery algorithm corresponds to a weighted vertex graph $G = (V, W, E)$ as shown in Figure 6. Here, the set of vertices $V = \{v_1, v_2, ..., v_n\}$ represents the n participants locations, the vertices weights set $W = \{b^t_1, b^t_2, ..., b^t_n\}$ represents the sample's prices at time t, and the set of edges E represents the connection between pairs of vertices. Thus, every vertex j connected by an edge to the vertex k is called the neighbor of k.

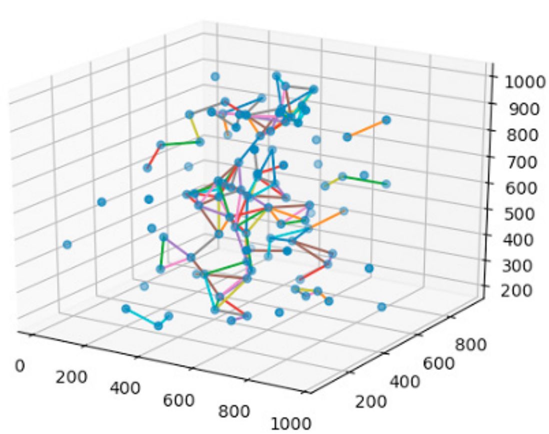


Fig. 6. Output of Discovery Algorithm

Dealer Decision Algorithm (DDA) : the Dealer Decision Algorithm uses information of the previous round bids of each participant and its neighbors to predict which player would win the current round. These players are then designated as "dealers" and will offer deals to their neighbors. Players that are predicted to lose are "nondealers" and will receive deals from any number of dealer neighbors. Players without any neighbors will be designated "isolated" and operate based on their previous round status according to the behavioral model specified by RADP-VPC-RC Lee and Hoh (2010). This model specifies that winners will increase their bid price by 10% with a probability of 50%, and the losers will reduce their bid by 20%

Algorithm 1 Dealer Decision Algorithm (DDA)

input: $For\ player\ n_j\ :\ b^{r-1}_j - previous\ bid, b^{min}_j - minimum\ bid, c_j - Cardinality(No.\ of\ neighbors)$
output: $behavior$

if $c_j == 1$ **then**
  $behavior \leftarrow isolated$
else if $b^{r-1}_j == b^{min}_j$ **then**
  $behavior \leftarrow dealer$
else
  $behavior \leftarrow nondealer$
end if
return $behavior$

Dealer negotiation algorithm (DNA) :Describes our proposed DNNA model. if a player is designated as a dealer it will offer deals to all of its l neighbors in the hope of winning in the current round. In fact, the dealer offers a portion of its predicted profit, d^i_j, to its neighbor n^i_j hoping to convince n^i_j not to modify its bid price, which would allow the dealer to win (see equation 1).

$$d^i_j = \frac{r_i}{\sum_{k=1}^{l} \frac{1}{b^{t-1}_{n^i_k}}} \times \frac{1}{b^{t-1}_{n^i_j}} \tag{1}$$

In equation 1, r_i corresponds to the difference between bid price of the dealer, b^{t-1}_i, and $(tV_i + \gamma_i)$, where tV_i and γ_i are the true valuation and the minimum profit that participant i is willing to accept, respectively. According to equation 1, the dealer offers a weighted portion of the obtained profit to each of its neighbors that is proportional to each neighbor's bid price.

Algorithm 2 Dealer negotiation algorithm (DNA)

input: $for\ player\ n_j\ and\ neighbors\ \{n_1...n_l\}\ :\ tV_j - player\ true\ valuation, \gamma_j - minimum\ profit, b^{r-1}_j - previous\ bid, b^{min}_j - minimum\ bid, R_j - risk\ factor$
output: $bid\ price\ and\ offer$

$r_j \leftarrow b^{r-1}_j - (tV_j + \gamma_j)$
for $each\ neighbor\ n_k$ **do**
  $d^k_j \leftarrow (r_j / (\sum_{i=1}^{l} 1/n^{r-1}_i)) * 1/b^{r-1}_{n_k}$
  $decision \leftarrow OfferDeal(d^k_j, n_j)$
end for
if $decision == accept$ **then**
  $b^r_j \leftarrow (b^{min}_j - b^{r-1}_j) * (R_j - 1) + b^{r-1}_j$
else
  $b^r_j \leftarrow (b^{r-1}_j - tV_j - \gamma_j) * (R_j - 1) + b^{r-1}_j$
end if
return b^r_j

The function *offerDeal*(d^i_j, n^i_j) in Algorithm 3.3.4 takes two parameters: The dealer's offer d^i_j and its the neighbor n^i_j, and outputs the neighbor's decision (i.e., *acceptance* *or rejection*). If all the neighbors of a dealer accept the offer, then, the dealer sets its bid price for round t using a simple linear function (see equation 2) which takes into account its bid price in round $t-1$ and $min\{b_{n_1^i}^{t-1}, ..., b_{n_l^i}^{t-1}\}$ according to a risk factor associated to each participant. We assigned to every participant i a random risk factor $R_i \in [0, 1]$ sampled from a uniform distribution that represents the amount of greediness.

$$b_i^t \leftarrow (min\{b_{n_1^i}^{t-1}, ..., b_{n_l^i}^{t-1}\} - b_i^t) \times (R_i - 1) + min\{b_{n_1^i}^{t-1}, ..., b_{n_l^i}^{t-1}\} \quad (2)$$

$$b_i^t \leftarrow (b_i^{t-1} - tV_i - \gamma_i) \times (R_i - 1) + b_i^{t-1} \quad (3)$$

Dealer Neighbor Negotiation Algorithm (DNNA) : Here, non-dealer participants can be surrounded by several dealers, thus, it waits until it receives offers from all the dealers. The acceptance or rejection criteria depend on the following factors. If the sum of the offer of its neighbors is greater than γ_i, it accepts. However, if this is not the case, but at least one of its neighbor's bid price is less than the participant's $tV_i + \gamma_i$, then it accepts. Finally, if none of the previous conditions are met, then the algorithm determines that the participant should reject.

Algorithm 3 Dealer neighbor negotiation algorithm(DNNA)

input: *for player* n_j *and neighbors* $\{n_1...n_l\}$: tV_j − *player true valuation*, γ_j − *minimum profit*, b_j^{r-1} − *previous bid*, b_j^{min} − *minimum bid*, b_j^{max} − *maximum bid*, d_j^l − *deal offered by neighbor* l, R_j − *risk factor*
output: *bid price*

$sum \leftarrow \sum_{k=1}^{l} d_j^l$
if $sum > \gamma_j$ **then**
  $decision \leftarrow accept$
else if then
  $decision \leftarrow accept$
else
  $decision \leftarrow reject$
end if
if decision == accept **then**
  $b_j^r \leftarrow b_j^{r-1}$
else
  $b_j^r \leftarrow (b_j^{r-1} - tV_j - \gamma_j) * (R_j - 1) + b_j^{r-1}$
end if
return b_j^r

Hence, if the decision of the participant is to accept, it will not modify its bid price at round t; the bid price will the same as that of round $t-1$. However, if the decision is to reject, the bid price is set as the equation 3.

Platform Winner Determination (PWD) Finally, the platform computes the winner after each round by combining the RADP-VPC-RC Lee and Hoh (2010), and the greedy budgeted maximum coverage algorithm Khuller et al. (1999). This combination takes the form of the GIA Jaimes et al. (2012) which we used in the paper as a general framework. Thus, if a participant is classified by the Dealer Decision Algorithm as isolated (no neighbors around) the participant will assume by default the behavioral model of GIA. On the other hand, if the participants are classified as a dealer or a non-dealer, then the participant behavioral model will be dictated by the Dealer Decision algorithm, and the Dealer Neighbor Decision algorithm respectively.

4. PERFORMANCE EVALUATION

4.1 Experimental setup

A complete virtual environment was implemented in Virtual Robotis Environment (VRep) to be able to observe the performance of the proposed algorithm and thus compare it in the auction system when the proposed algorithm is not applied. An environment with buildings, trees, people, and a swarm of UAVs was implemented. VRep was used because this is a system for the simulation of robotics environments and allows the instantiation of 100 robots at the same time. In this case, about 50 drones that navigate autonomously and actively participate in the auction were used. The volume of interaction space is $400,000m^3$ with 6 buildings and several trees and people, as shown in figure 1. These AUVs perform the primary surveillance task and in the background, they execute the UAV-Crowdsensing mission without affecting the primary task.

4.2 Experiments

Experiment 1 The goal of this experiment is to explore the effects of the budget on the percentage of coverage. Here, we increase the budget capacity from 100 to 91400 in multiple steps with a step size of 200, while keeping fix the sensor radius (300 units).

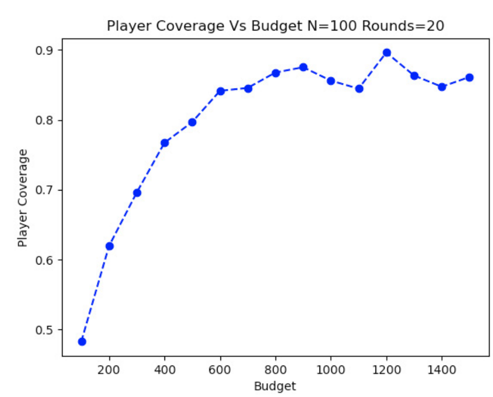


Fig. 7. Budget vs Coverage

Figure 7 shows the coverage results after 20 rounds. In this case, the figure shows that coverage scales very well. However, after a budget of 800, there are no significant gains in terms of participants' coverage.

Experiment 2 Keeping a minimum number of active participants is a fundamental issue for incentive mechanisms based on the reverse auction. Usually, if a participant is not able to recover the Return of Investment (ROI) after a few rounds, it will end up dropping out from the system.

This phenomenon causes exponential increases in the bid prices, due to the lack of competition among the survivor's participants. Figure 8 shows steady increases of active participants as a result of increases in the budget.

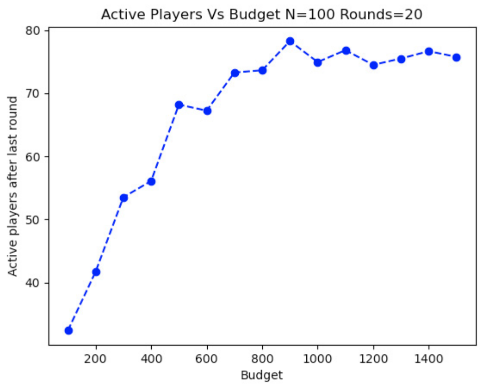


Fig. 8. Budget vs Percentage of Active Participants

Experiment 3 The goal of this experiment is to determine the ideal length of the radius (R). Here, the radius represents the sensing capacity of the onboard sensor of a UAV. In order to study the relationship between the radius R and the number of active participants, the length of R was increased from 100 to 500 in steps of 100. Twenty rounds were executed and the results are presented in Figure 9.

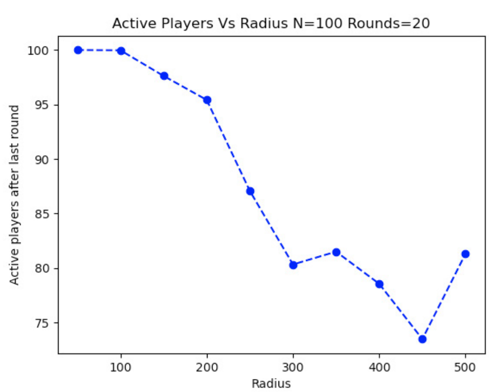


Fig. 9. Radius vs. number of active participants

Figure 9 shows the trade-off between the radius and active participants. For small values of R, the participants are classified as isolated. On the other hand, for larger values of R participants start to have neighbors (cover other participants within its sensing range) and thus, the crowdsourcer just buys a sample from that neighborhood avoiding the acquisition of redundant samples. For all the experiments we set the value of R to 300. (the elbow of Figure 9).

5. CONCLUSION

We design and evaluate an incentive mechanism for UAVs crowdsensing. The proposed mechanism uses a recurrent reverse auction, and an optimization mechanism to acquire a set of samples that maximize coverage within a limited budget. Unlike most the current crowdsensing systems, the proposed approach is based on cooperation rather than competition. This cooperation has the form two algorithm, namely the dealer negotiation, and the dealer negotiation algorithms. After extensive simulations, we show that our mechanism performs very well in terms of sensing coverage, and participant retention while minimize the cost.

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