Recharging wireless sensor networks using drones and wireless power transfer

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***Abstract*—In this paper, we tackle the optimal energy replenishment problem (OERP) using a given number of flying drones, in order to efficiently recharge wireless sensor nodes. We present a linear program that maximizes the amount of harvested energy to the sensors. We show that the model is solved to optimality in a few seconds for sensor networks with up to 50 nodes. The small number of available drones is shown to be optimally deployed at low altitude in order to efficiently recharge the batteries of at least half of the sensor nodes.**

I. THE OPTIMAL ENERGY REPLENISHMENT PROBLEM

Wireless sensor networks are capable of periodically monitoring their vicinity and reporting important information about the integrity and security of their environment. Sensors are powered by batteries and depending on how often they take measurements and communicate with other devices, their energy may be depleted fast. Battery replacement may be a hard task since the nodes are often positioned in inaccessible places or the cost of replacement may be high. To tackle this problem, a new technology has been recently developed by harvesting energy from the transmitted RF signals [1]. This technology uses a new type of antenna which can convert part of the received signal power to electricity. Depending on the transmitted power and the distance between the transmitting source and the receiver, a node can harvest from some uW to some mW of power.

In this paper, we study the problem of optimally deploying drones that can fly over the sensor area and directionally emit energy towards the sensors to recharge their battery. Recent works have considered using drones as chargers to enhance wireless sensor network lifetime. They often limit the problem in a two-dimensional space [2] or consider only a one-to-one recharger model [3]. [4] provides only approximated solutions, and [5] minimizes the number of drones to maintain the network for a given amount of time. Results of [5] show that the optimal number of drones is high and usually unrealistic. We thus develop an optimal model with a dual objective to tackle this issue.

Given a fixed number of available drones, the goal is to deploy them in the 3D-space to provide optimal recharging capabilities to sensors. We split the time in rounds where each round has two phases: the recharging phase and the operation phase. During the operation phase, a sensor consumes energy for classic operations such as sensing and data transmission, modeled by a priority function taking into account battery level, number of predecessor nodes, distance to the sink, ... During the recharging phase, it gets recharged by fake data transmission from the drones, depending on the needs during the operation phase and the harvesting speed. We assume that the amount of data to be transmitted and the sensing operation have fixed and known duration, we thus focus on the harvesting effectiveness.

A. Energy harvesting model

We adopt the model used in [5] where the energy harvested by node i during time period length t, while it is in the harvesting range of drone j is given by :

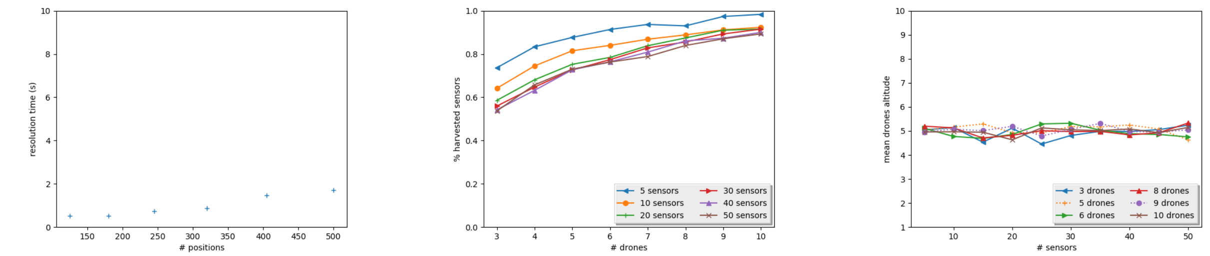
$$H_i^t = P_0 \frac{e^{2\sigma G}}{(d_{ij})^{2b}} \cdot f^{d_{ij}} \cdot \frac{pk_e}{dr} \cdot t,$$

where $P_0 \frac{e^{2\sigma G}}{(d_{ij})^{2b}} = P_{rx}^{d_{ij}}$ is the received power depending on the following propagation model: $e^{2\sigma G}$ has a log-normal distribution with a shadowing coefficient $\sigma(G \sim N(0,1))$, and the term $1/(d_{ij})^{2b}$ accounts for the far-field path loss with distance d_{ij}, where the amplitude loss exponent b is environment-dependent. P_0 is the received power at reference unit distance. $f^{d_{ij}}$ is the efficiency of the harvesting antenna at distance d_{ij} provided by the manufacturer Powercast[1]and the decomposition into piecewise linear functions[2], and k_e is the number of fake packets transmitted per time period.

B. Optimization model

Given $\mathcal{N}$ the set of drones, $\mathcal{J}$ the set of possible 3D-positions, and $\mathcal{I}$ the set of sensor nodes with their associated priority P_i, we define x_n the binary variable stating if drone $n \in \mathcal{N}$ is deployed. For each drone, we then associate the time t_j^n during when it is located at position $j \in \mathcal{J}$. The goal is to maximize the amount of energy harvested from the deployed drones to the sensors, while fulfilling the budget (in terms of number

[1]http://www.powercastco.com/wp-content/uploads/2016/12/P2110B-Datasheet-Rev-3.pdf
[2]http://ulr.gforge.inria.fr/



(a) Resolution time vs. nb of 3D-positions.

(b) Percentage of recharged sensors.

(c) Mean altitude of deployed drones.

of drones) B and recharging phase time τ limits. We also specify that at most one drone can be placed at each 2D-position at the same time, determining one possible altitude. The linear program is thus the following:

$$\max \sum_{n\in\mathcal{N}} \sum_{j\in\mathcal{J}} \sum_{i\in\mathcal{I}} P_i H_i^{t_j^n} \tag{1}$$

$$\sum_{n\in\mathcal{N}} x_n \leq B \tag{2}$$

$$\sum_{j\in\mathcal{J}} t_j^n \leq \tau x_n, \forall n \in \mathcal{N} \tag{3}$$

$$\sum_{n\in\mathcal{N}} \left(t_j^n + \sum_{j'\in\mathcal{J},(x_j,y_j)=(x_{j'},y_{j'})} t_{j'}^n \right) \leq \tau, \forall j \in \mathcal{J} \tag{4}$$

$$x_n \in \{0,1\}, t_j^n \in \mathbb{R} \tag{5}$$

II. Results

We have implemented the model in Java language and solved using IBM Cplex solver 12.7.1 on an Intel(R) Core(TM) i7-5500U CPU, 2.40 GHz, 16 Gb RAM machine, under Microsoft 8.1 Pro operating system.

A. Data inputs

Instances are deployed in a square area of size $50m \times 50m$. We choose randomly the sensors 2D-coordinates and divide the area into equal squares such that the positions for placing a drone form a regular grid. For each point (x_p, y_p), we set the allowed altitudes to $\{1m, 2m, 5m, 7m, 10m\}$. We then generated instances of size between 15 and 50 sensors, 3 and 10 drones, and 125 and 500 possible 3D-positions. The sensors priority is equal to their density of neighbors within 2m. For each size of $\mathcal{I}$, $\mathcal{J}$ and $\mathcal{N}$, we compute 10 different random topologies. We summarize results with the mean value for each topology size. The chosen parameters for the harvesting model are $P_0 = 10mW$, $\sigma = 0.1$, $k_e = 150$ packets/sec, $p = 127bytes$, $dr = b = 1$, and $\tau = 30min$.

B. Deployment evaluation

We first remark that the model is solved to optimality in less than 2 seconds for all topologies (Fig. 1a). This is of great interest to determine theoretical bounds of OERP. Then, the drone deployment provides good harvesting capabilities since it allows to recharge at least 55% of the sensor nodes with only 3 drones (Fig. 1b). And with 8 drones, 80% of sensors can harvest energy during the recharging phase. Finally, we look at the altitude of the deployed drones in Figure 1c. Deploying drones at lower altitude ensures better harvesting capabilities. Given the possible altitudes, we see that the mean altitude is always located around 5m for all the topologies. This means that, even if we need to deploy some drones at high altitude (10m) to recharge an important number of sensors, we still have drones usually located at 1, 2 or 5m, which validates our model for effective energy replenishment. The results also show that it is better to let the drones in a stationary state at the best locations, instead of moving from one location to another during the recharging phase.

III. Conclusion

We have presented an optimal linear formulation for the energy replenishment problem, deploying a given number of drones in order to recharge sensor batteries. The model can be solved to real-sized instances in few seconds. Results show that the use of drones to simultaneously recharge more than half of the sensors batteries during the recharging phase is efficient. They also show that the drones altitude is minimized to ensure good harvesting capabilities, and that it is better to let the drones in a stationary state at the best locations, which gives good insights to the analysis of practical distributed algorithms and industrial scenarios.

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