Multi-agent Scheduling Optimization in Dynamic Environments under Energy Constraints

Doctoral Consortium

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ABSTRACT

Our research considers the problem of enabling persistent execution of a multi-drone task under energy limitations. The drones are given a set of locations and their task is to ensure that at least one drone will be present, for example for monitoring, over each location at any given time. Because of energy limitations, drones must be replaced from time to time, and fly back home where their batteries can be replaced. Our goals are to identify the minimum number of spare drones needed to accomplish the task while no drone battery drains, and to provide a drone replacement strategy.

KEYWORDS

Multi-Robot Systems; Multiagent Scheduling; Task Allocation

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1 INTRODUCTION

Aerial drones are emerging as an effective and efficient tool for monitoring and surveillance. Applications include civil security operations, continuous surveillance of a disaster scene such as flooding and forest fires [12], traffic monitoring [7], and event photography [15]. The main limitation in deploying drones for such applications is their short flight times: commonly used drones, equipped with even minimal sensors, have a maximum flight time of approximately 20 to 30 minutes, usually less than that. To overcome this severe limitation in persistence monitoring tasks, spare drones should be available to replace drones that are running low on battery. The replaced drones could fly to a location where their batteries can be charged or replaced, enabling them to continue in their task [13]. To our knowledge, this research concentrate on a problem that has not yet been considered so far, in two aspects: (i) Persistent operation, in the sense of non-stop continuous service. (ii) Determining the minimal number of robots to accomplish the persistent operation, from an energetic point of view. While this research focus is the possible solutions for persistent monitoring for drones, it is valid for *any* robot type having energy constraints, performing *any* persistent task, as long as the travel cost of the robots in the environment satisfies the triangle inequality. The various existing approaches for multi-robot persistent task performance lack one or both of the two aspects, addressed in our research. Among them are the variants of the Vehicle Routing Problem (VRP) [1, 2, 4, 8–11, 14].

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2 MINIMAL SPARE DRONE FOR PERSISTENT MONITORING PROBLEM, MSDPM

The drones are given a set of locations l of k locations, $l = \{l_1, l_2, \dots, l_k\}$. We define the Minimal Spare Drone for Persistent Monitoring Problem, MSDPM, for determining the minimal number of spare drones, as well as finding a schedule of drone replacements that guarantees both that the persistent monitoring tasks are fulfilled indefinitely, and that no drone battery is drained. Thus drones must be replaced with enough energy to return safely to their home denoted by h_1 for battery exchange. The required number of drones necessary to ensure persistent monitoring is greater than k. We refer to the p extra drones, that is, the drones used for replacing the drones in the monitoring task, as *spare drones*. There are several cases for the MSDPM problem, some of them (2,4,7,8) we'll consider in future work: (1) Homogeneous drones. (2) Heterogeneous drones. (3) One home for battery exchange. (4) Several homes for battery exchange. (5) Off-line, the set of location l is given in advance. (6) On-line, the set of locations is given one by one over time. When a location is given it must be assigned immediately to one of the spare drones, which are added as needed. (7) Dynamic, locations may be discarded or changed. (8) Drones may be cut off due to technical problems or attack.

The formal definition of the MSDPM in the case of homogeneous drones with one home is as follows:

> *Given a set of k locations that require persistent monitoring, a set of $k+p$, $p > 0$ homogeneous drones with maximal battery capacity $L < \infty$, and one home location h_1 in which the drones replace batteries. Determine whether the p spare drones are sufficient for assuring that each location is monitored indefinitely by at least one drone, and that no drone's battery will drain unless it is in h_1.*

The above description is the decision-version of the MSDPM problem. Our goal is to find the minimal number of spare drones satisfying the persistent monitoring task, that is, the minimal number p^* such that MSDPM is true. In the full paper [6] we give detailed full definitions and proofs. The *drone replacement pattern* (or *drone replacement*, in short), is the possible scheduling of replacements of drones at each l_i. The drone replacement patterns set the building blocks for analysis of the MSDPM problem. We distinguish between four different switch types of possible drone replacements at location l_i. To encompass all possibilities of drone replacements we define a mathematical notation: *replacement scheme $R = (i_1, i_2, \dots, i_j, \dots, i_{k_1})$ is a series of time consecutive drone replacements until all the batteries of all k drones are replaced at h_1.* R=(2, 1, 3, 4, 5, 2, 1, 3, 4, 5, 5) is the

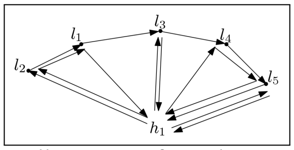

Figure 1: An illustration of a replacement scheme.

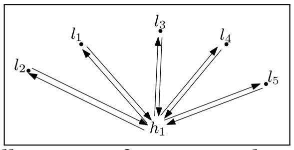

Figure 2: An illustration of a proper replacement scheme.

replacement scheme illustrated in figure 1, R^S=(B, C, C, C, D, B, D, A, B, D, A) is the corresponding series of replacement switch types. R^T=(10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110) can be the corresponding series of replacement timings, if all travel times equal 10 time units. A replacement scheme in which drones goes only back and forth to h_1 is most useful, and we refer to it as a *proper replacement scheme.* $R = (2, 1, 3, 4, 5)$ is the proper replacement scheme illustrated in figure 2.

3 PRELIMINARY RESULTS

The following theorem gives the general requirement on the battery capacity of the drones, L, to enable k drones to perform persistent monitoring on a set of locations l with a single spare drone. We denote by c the rate of discharge per time unit. $\underline{t}_i := \dfrac{dist(l_i, h_1)}{v}$ is the drone's travel time between h_1 and l_i. Therefore $c \cdot \underline{t}_i$ is the amount of charge units it takes a drone to get from h_1 to l_i.

Theorem 3.1. *In order to keep persistent monitoring on a location set l using the set of $k+1$ drones with maximum battery charge L, it is sufficient and necessary that the following requirement be satisfied:*

$$L - 2c \cdot \underline{t}_i \geq \sum_{j=1}^{k} 2c \cdot \underline{t}_j \quad \textit{for } i = 1, \dots, k$$

If the requirement is satisfied, then any proper replacement scheme guarantees that the persistent monitoring task will be performed indefinitely. If the requirement is not satisfied, then one spare drone is *not* enough for performing persistent monitoring over the given locations. Thus this requirement solves the MSDPM problem for $p = 1$.

When one spare drone is not enough, we can find the minimum number of spare drones p, and allocate locations to the spare drones, by solving a variation of the Bin-Packing problem with an additional constraint: in each bin, items are packed such that the maximum item in this bin is packed twice. The reason for this is that by a Lemma we prove in [6], If p spare drones are needed in order to keep persistent monitoring on locations set l, using a set of $k + p$ drones with maximum battery charge L, performing any series of drones replacements, then it can also be achieved by dividing l into p disjoint subsets $l = S_1 \uplus S_2 \uplus \dots \uplus S_p$ such that for each subset S_i, persistent monitoring is achieved using one spare drone to repeatedly perform a proper replacement scheme over the locations in S_i. The requirement of theorem 3.1 implies that in each set, each drone, and in particular the one with maximum distance from h_1, has to wait for all other drones to be replaced by a spare drone which travels back and forth to h_1, and then travels back and forth to h_1 one more time to start the next replacement scheme. The items to be packed are the battery charge amounts: $2c \cdot \underline{t}_1, 2c \cdot \underline{t}_2, \dots, 2c \cdot \underline{t}_k$. We name this new variant *Bin Maximum Item Doubled Packing* (BMIDP). We consider two versions of the BMIDP problem: (i) The *offline* version, in which all items are known in advance. It solves the offline version of the MSDPM problem where the set of locations is given in advance; and (ii) The *online* version, in which items are given one by one. It solves the online version of the MSDPM problem where the locations are given one by one over time. Since Bin-Packing is NP-Hard [3, 5], BMIDP is presumably hard as well. Therefore: (i) We adjust First Fit (FF) online Bin-Packing approximation and call it Max Item Doubled First Fit (MIDFF) for the BMIDP *online* version; (ii) We adjust First Fit Decreasing (FFD) offline Bin-Packing approximation and call it Max Item Doubled First Fit Decreasing (MIDFFD) for the BMIDP *offline* version.

For MIDFFD we prove an approximation factor ≤ 1.5: *theorem. Max Item Doubled First Fit Decreasing (*MIDFFD*) uses at most 1.5B bins if the optimal packing for* BMIDP *(OPT) uses B Bins.*

For MIDFF we hypothesize that the approximation factor is ≤ 2 and show an average approximation factor of 1.7 via extensive experiments with various parameter settings. In order to avoid intractable computation of the BMIDP optimal value, we used the minimal number of spare drones instead of OPT. Therefore the approximation factor our experimental results yields is a strict upper bound of the real approximation factor. In all the graphs, upper line is the MIDFF results and lower (better) is the MIDFFD.

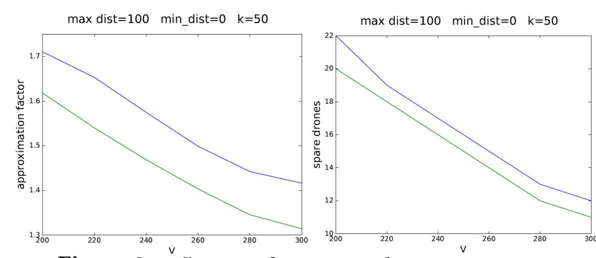

Figure 3: Influence of increasing battery capacity L.
(a) expr. approx. factor (b) spare drones

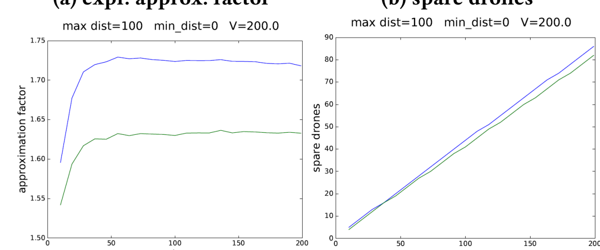

Figure 4: Influence of increasing k, the number of locations.
(a) expr. approx. factor (b) spare drones

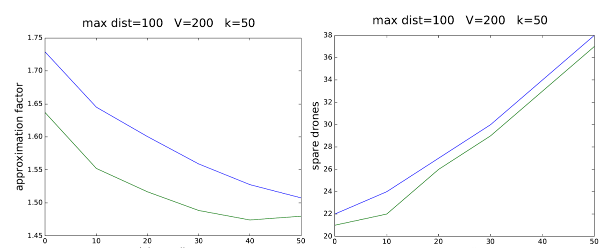

Figure 5: Influence of increasing the minimum distance from h_1.
(a) expr. approx. factor (b) spare drones

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