Multi-agent Task Allocation for Fruit Picker Team Formation

Extended Abstract

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ABSTRACT

Multi-agent task allocation methods seek to distribute a set of tasks fairly amongst a set of agents. In real-world settings, such as fruit farms, human labourers undertake harvesting tasks, organised each day by farm manager(s) who assign workers to the fields that are ready to be harvested. The work presented here considers three challenges identified in the adaptation of a multi-agent task allocation methodology applied to the problem of distributing workers to fields. First, the methodology must be fast to compute so that it can be applied on a daily basis. Second, the incremental acquisition of harvesting data used to make decisions about worker-task assignments means that a data-backed approach must be derived from incomplete information as the growing season unfolds. Third, the allocation must take "fairness" into account and consider worker motivation. Solutions to these challenges are demonstrated, showing statistically significant results based on the operations at a soft fruit farm during their 2020 and 2021 harvesting seasons.

KEYWORDS

multi-agent system; multi-robot system; task allocation; fruit harvesting

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1 INTRODUCTION

Due to the increasing demand for soft fruits and shortages in seasonal workers [4, 9, 11], farms are requiring innovative solutions for managing their workforce during the fruit harvesting season. Typically, on such farms, each day a harvest manager determines which fields are ready for picking, how many "team leaders" (and thus teams) there will be, and which workers should be assigned to each team. Managing hundreds of seasonal workers with various skill levels is a time consuming process. To prevent crop loss, maximise yield and minimise staff time, workers are frequently organised into groups or "teams" and this must be done efficiently.

Our aim is to automate the process of assigning workers to fields, attempting to optimise the performance of a given workforce each day. Our longer term aim is to develop a methodology that will allow a farm to easily integrate robots in their workforce. In the not-too-distant future, robots may soon be filling gaps in the shortages of seasonal workers [2, 9, 10, 14, 15]; and therefore, robotic co-workers will need to be managed alongside the human workforce. In [6], we explored how to manage a team of workers within the field. Here we investigate how to assign workers to a team each day. In both these works, the worker's (agent's) species is agnostic: human or robot. Hence we anticipate the ability to adopt our methodology seamlessly for human-only and human-robot workforces.

A key challenge in multi-agent and multi-robot systems is to decide which *tasks* should be assigned to which agents (or robots) so that the overall execution of a *mission* (set of tasks to be executed within a particular overall timeframe) is *efficient*: resources are used effectively, so that time and energy are not wasted and, often, some reward is maximised. Many different types of *task allocation* mechanisms (such as auction-inspired approaches [3, 7, 8, 12]) have been explored within the multi-agent systems (MAS) and multi-robot systems (MRS) communities, generally addressing what are referred to as *multi-robot task allocation (MRTA)* problems.

2 METHOD

Our method involves two steps: (i) creating an initial solution using a modified version of Round-Robin (RR); and (ii) improving the solution to minimise the variance across estimated per-field harvest times. This section presents our base method and three variants.

2.1 Create Initial Solution

2.1.1 Standard RR. To create an initial solution, we implemented a standard RR scheduler due to its low computational cost [13]. We first order the fields and workers, considering fields as bidders and workers as items. Workers are sorted slowest first, using their average picking speed over all fruits. Fields are sorted by yield (lowest first). RR assigns the first item (worker) to the first bidder (field), the second to the second bidder and so on. After one task has been assigned to each bidder, the bidders are iterated over to assign each a second task, and so on until all tasks have been allocated.

2.1.2 Repaired RR. During some of our experiments, we found that a high proportion of the pickers were assigned to fields containing fruit that they had no prior experience of picking. We therefore modified the RR scheduler so that a worker is only assigned to a field containing a type of fruit that the worker has picked before. This algorithm results in each field having (roughly) an equal number of workers assigned to it.

2.2 Improve Solution

The second step in our method improves the solution by reassigning workers from fields requiring less picking time to fields requiring more picking time. The method implemented also aims

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to keep the staff time down, and maintain a mix of highly-skilled and low-skilled workers within a single field. This section outlines the specifics of reducing the difference in picking time between the fields, followed by two improvements to this method.

2.2.1 Δept-smoothed variant. This variant involves first computing the **estimated picking time** (ept) for each field (f) for a particular date (d), assuming it is picked by a specific team of workers (W). This is calculated by dividing the *estimated yield* (for field f on date d) by the sum of the workers' picking speeds ($w.ps$), as shown in Equation 1:

$$ept(f, W, d) = \frac{f.estimated\_yield(d)}{\sum_{w \in W} w.ps(f.\text{fruit})} \tag{1}$$

We start with a list of pairs of fields that is sorted by the difference in estimated picking time between the two fields (Δept). The pair of fields with the largest Δept appears first, and the rest are taken in descending order of Δept. Then the algorithm searches for the picker who, when moved from the field with the shortest picking time to the field with the longest picking time (in each pair of fields), produces a reduced Δept. We call this the "candidate worker". If no worker is moved (i.e. because moving a worker would increase Δept or the field with the shortest duration has two or fewer workers), then the pair of fields is removed from the list of all pairs of fields. The algorithm continues until the list of pairs of fields is empty.

2.2.2 Δept-repaired variant. In executing the method described in Section 2.2.1, workers with a high picking speed could be moved to a field containing a fruit they are less skilled at, to decrease the execution time of the field they were moved from. This could result in the worker being assigned a type of fruit they have no experience of picking. To prevent this situation, we modified the baseline algorithm as follows. After a candidate worker (to move) has been identified, the algorithm compares all remaining workers to the candidate. If the candidate worker is not skilled and another worker (being considered) has experience (and the difference in picking time, Δept, is still lower), then the alternative worker is selected (and becomes the candidate). If both workers have experience, then the worker with the (positive) largest difference in picking speed will be selected. For example, if worker A has a picking speed of 0 for fruit p and 5 for fruit q, and worker B has a picking speed of 3 for fruit p and 1 for fruit q, then worker A will be moved to pick fruit q.

2.2.3 Balanced variant. To maintain a balance of fast/slow pickers across the fields, if the fields contain the same fruits, then we compare the mean picking speeds of both fields and check this against the worker's picking speed. The aim of this step is to keep the mean picking speeds of the fields similar, e.g. so that all the "champion" (best) pickers are not grouped into a single team. This seems to result in higher overall satisfaction across the team of workers, as reported by farm managers.

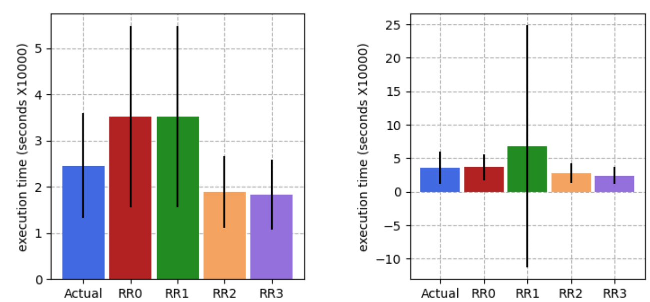
2.3 Experiments and Results

Our experiments are performed on the data provided by a large commercial fruit farm. Historic data from the whole of the 2020 picking season (175 picking days) for strawberry and raspberry fields (25 field in total) has been provided. For 2021, cherries and blackberries are also included. For the 2021 picking season, data was provided incrementally; results presented here are for up to 6th September 2021, which involved 117 picking days and 29 fields. An experiment consists of running each method variant (below) to compute the estimated picking times per day across each season.

Our baseline is the **Actual** teams that were deployed by farm managers during each day of each picking season (2020 and 2021). Four variants of our method are compared:

- **RR0** The standard RR algorithm, described in Section 2.1.1.
- **RR1** The repaired RR algorithm, described in Section 2.1.2.
- **RR2** The Δept-smoothed variant (described in Section 2.2.1), modifying the output of RR0. When just using the Δept-smoothed variant, the candidate worker that reduces the Δept the most is moved.
- **RR3** The combined variant, modifying the repaired RR output (labeled RR1 above), using the Δept-smoothed (described in Section 2.2.1), repaired (Section 2.2.2) and balanced (Section 2.2.3) improvements.

As shown in Figure 1, the combined variant (**RR3**) produces the lowest execution time (difference between the start and end times of each day, based on the ept) in comparison to the alternative methods. This result is statistically significant for both data sets.



(a) 2020 historic data (F=60.10, p=0.000)

(b) 2021 live data (F=5.09, p=0.000)

Figure 1: Execution time and ANalysis Of VAriance (ANOVA) [1, 5] statistics.

3 CONCLUSION

This paper explores automating the daily process of assigning pickers to the fields of a soft fruit farm, a process which is currently performed manually by farm managers. We developed several variations on the standard Round Robin method of distributing tasks to agents and compared our approach to the teams actually deployed by a commercial fruit farm. The difference in execution time between the actual teams and four variants of our method is statistically significant. Our combined variant methodology (RR3) produced the lowest execution time.

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