Challenges for Multi-Agent Based Agricultural Workforce Management

Helen Harman[0000−0002−3195−2579] and Elizabeth I Sklar[0000−0002−6383−9407]

Lincoln Institute for Agri-food Technology, University of Lincoln, Lincoln, UK
{hharman,esklar}@lincoln.ac.uk

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 soft fruit farms, human labourers undertake harvesting tasks, assigned by farm managers. The work here explores the application of artificial intelligence planning methodologies to optimise the existing workforce and applies multi-agent based simulation to evaluate the efficacy of the AI strategies. Key challenges threatening the acceptance of such an approach are highlighted and solutions are evaluated experimentally.

Keywords: agriculture · multi-agent based simulation · task allocation

1 Introduction

On farms that grow high-value crops, such as soft fruit (e.g. strawberries, raspberries, cherries), field vegetables (e.g. broccoli, cauliflower) and ornamentals (e.g. daffodils), seasonal workers are hired to pick ripe produce at harvest time. Shortages in seasonal labour, due to a variety of global political, social, economic and health factors [4, 13, 19] are motivating farmers to seek innovative solutions for managing their harvest workforce—otherwise, farms may be left with plants unharvested, which is both costly and wasteful [20]. To help address this situation, we have been exploring the application of *artificial intelligence (AI)* planning methodologies to optimise the existing workforce and *multi-agent based simulation (MABS)* to evaluate the efficacy of our strategies. Although our methods and simulation results are backed by real-world data sourced from a commercial farm, there are a number of key challenges that we have faced along the way that could threaten the acceptance of such an approach. Here we describe these challenges and present our solutions designed to mitigate their impact.

The first challenge is centred around how to handle the different types of incrementally produced data so that our solution can be deployed when it is needed. In general, there are two types of data that we can obtain from farms: *historic* data, which records what happened in the past; and *prognostic* data, which estimates what will happen in the future. Most modern farms maintain detailed historic electronic records describing the resources expended and labour activities, helping farm managers to minimise costs in a sector that traditionally operates at very low margins and with high risk due to dependence on the weather. In order to plan ahead—on a daily basis as well as seasonally—farmers also develop detailed estimates describing when crops should be planted, tended and harvested. This includes associated volumes and locations, as well as the size and skills of the labour force required to accomplish the planting, crop care and harvesting tasks.

The second challenge relates to the application of multi-agent based simulation to assess the impact of our proposed AI planning strategies for managing the workforce versus the manual strategies currently employed on farms. Typically, this involves farm managers wrangling spreadsheets in order to determine who is available on any given day to perform the range of tasks that must be completed. While farms do record many aspects of harvesting, they do not record details that would better inform a more accurate simulation of workforce, such as tracking where individuals walk in fields and when they take breaks. Although it is technically possible to record such data, this is not something that workers are happy about—being watched by "big brother" is uncomfortable, especially for many migrant workers, and could cause workers to quit their jobs and seek work on other farms where they are not being watched so closely. So we are challenged by wanting to show improvement within a simulation that is not a completely accurate portrayal of what is happening in the real world.

The third challenge is the workforce management strategy itself. In earlier work [6, 7], we explored different methods of assigning workers to fields and tasks to workers in the fields. Here we challenge some of the assumptions we have made in that work, particularly around modelling workers with no historic data.

This paper is organised as follows. Section 2 provides background on the specific fruit farm use case we simulate here and briefly discusses AI and multi-agent applications in agriculture. Section 3 describes the approach we have developed to address the challenges mentioned above. Sections 4 and 5 present our experiments and results. Section 6 summarises our work and highlights next steps.

2 Background

On soft fruit farms, each day during harvest season a farm manager determines which fields are ready for picking and how many groups of workers, or "teams", are needed. Each team harvests one or more fields; the manager decides which workers to assign to each team and which team to assign to each field. When fruit pickers arrive at the fields, team leaders assign picking areas for each worker. Pickers harvest ripe fruits and place them in containers held in trays; filled trays are then transported to packing stations where they are weighed and tallied to record the volume picked and by whom—often pickers are remunerated based on the volume of ripe fruits they pick. This picking information provides a rich data set from which a range of different models could be derived, including the multi-agent model developed here.

Potential opportunities for multi-agent and multi-robot methodologies applied within the agriculture domain are analysed and characterised in [16]. This includes use of autonomous robots to drive in fields and collect sensor data [4], which is analysed using machine vision methods to identify ripe fruit [11], map regions in need of irrigation [1], or locate weeds [15], as well as robotic solutions for picking and transporting crops [5, 14, 24]. Some researchers have experimentally evaluated hybrid human-robot solutions, where robots transport produce while humans do the picking [2, 23]. In our previous work [7], we showed how *Multi-Robot Task Allocation (MRTA)* strategies—evaluated using our simulator (see Section 3.3)—can be used to suggest the best ratio of "runners" (workers who transport produce) to pickers.

MRTA problems address situations in which a group of robots must work together to complete a set of tasks. A popular family of solutions to MRTA problems are market-based *auction mechanisms*. As described in the literature [3, 9, 10], auctions are executed in *rounds* that are typically composed of three phases: (i) announce tasks—an *auction manager* advertises one or more tasks to the agents; (ii) compute bids—each agent determines its individual valuation (cost or utility) for one or more of the announced tasks and offers a *bid* for any relevant tasks; and (iii) determine winner—the auction manager decides which agent(s) are awarded which task(s).

There is a substantial body of work on the application of auction-based mechanisms to the problem of allocating tasks for multi-agent teams. A popular method within the literature is the *sequential single-item (SSI)* method [12]. In SSI, all unassigned tasks are announced to the bidders and the bidder that responses with the best (e.g. shortest duration) bid for any task is allocated that task. The auction repeats in rounds until all tasks have been allocated. Auction mechanisms take into account both the self-interests of individual bidders as well as group goal(s) represented by the auction manager. Various variations on SSI have been proposed. Heap & Pagnucco [8] proposed *sequential single-cluster (SSC)* auctions for solving pick-up and delivery tasks in a dynamic environment. SSC announces and assigns *clusters* of geographically neighbouring tasks in each round, instead of only assigning one task (SSI).

Schneider et al. [22] conducted an empirical analysis of different auction-based mechanisms: SSI, *ordered single-item (OSI)*, *parallel single-item (PSI)* and *round robin (RR)* (as the simple baseline). Results revealed that the advantages of SSI can be greatly diminished when tasks are dynamically allocated over time. Subsequently, the performance of task allocation mechanisms in a set of parameterised mission environments was investigated [21]. Results showed that some task allocation methods consistently outperformed all others—but only under specific mission parameters. In the environments evaluated, no single method managed to outperform all others across all sets of parameters.

In our early attempts to address to the problem of assigning workers to fields (as outlined in Section 3.2), we compared SSI with RR. Although an in-depth investigation and comparison is planned in future work, our preliminary results showed more favourable performance with RR. Thus the approach presented here is based on RR. RR benefits from low computation costs and results in (roughly) even distribution of tasks (i.e. the number of tasks each agent is assigned differs at most by 1 when any agent is capable of performing any of the tasks on offer).

For MRTA problems, RR alone can result in inefficient task allocations. We therefore modify the output of RR to improve the solutions efficiency.

3 Approach

This section describes our overall approach in which we applied multi-agent based simulation to compare different methods of managing human labour on a soft fruit farm. First, we model the behaviour of individual workers. Second, we group workers into teams. Third we use a simulator to evaluate the teams.

3.1 Modelling Workers

We model human workers—fruit pickers—using a data-backed model, built on information that is already collected on many farms, as explained below. This "worker model" is based on an estimate of how quickly a picker harvests each type of fruit grown on the farm. Different types of fruit require different techniques for harvesting and thus different skills. For each type of fruit, each picker is assigned a different *picking speed*, in grams per second, computed for each type of fruit they have picked previously[1]. This is calculated by dividing the amount of fruit a picker picked by the duration the picker picked for, and finding the average over all dates they picked that type of fruit on.

If we encounter a worker who has not picked a certain type of fruit (i.e. does not have any historic information in our data set), we cannot assume that the worker is not able to pick that fruit. They could be a new worker whose experience is unknown to our system, or could be a worker who has never previously been assigned to a field with a particular type of fruit. To set the speed of these workers we cluster the pickers, using *k-means clustering* [18], and use the center of the cluster as the speed of all pickers in that cluster. When the clusters are sorted, this enables us to determine a rank (in $[0 \ldots (k-1)]$) for each worker (for each type of fruit they have picked). Our experiments look at the effect using a different default rank and clustering has on our results (see Section 5).

3.2 Team creation

Our team creation method involves two steps: (i) creating an initial solution using Round-Robin; and (ii) improving the solution to minimise the variance in the estimated field picking times across all fields. An overview of our method (and variations) has been presented in an extended abstract [6].

The first step in our method is to generate an initial solution, using RR. Workers are sorted slowest first, using their average picking speed over all fruits.

[1] Note that at least two trays of the same type of fruit must be recorded in order to calculate a picking speed for that fruit. If there are not at least two trays recorded in the data set, then the picker is assigned the default picking speed—like workers who have not picked any fruit of that type.

Fields are sorted by yield (lowest first). RR assigns the first worker to the first field, the second worker to the second field and so forth. After a single worker has been assigned to each field, the fields are re-iterated over to assign each of them a second worker, and so forth until all workers have been allocated.

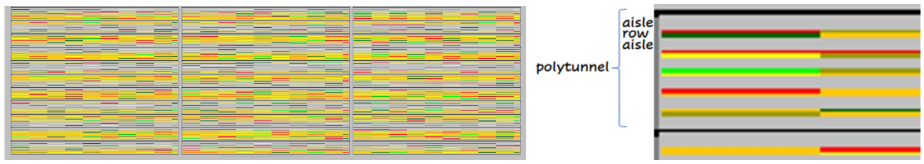
The second step in our method improves the solution by reassigning workers from fields requiring less picking time to fields requiring more picking time. This involves first computing the estimated picking time (ept) for each field (f) for a particular date (d), assuming it is picked by a specific team 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. After calculating the initial ept of each field, our approach creates 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.

3.3 Simulating Teams

We have constructed a *multi-agent based simulation* to evaluate the our proposed teams and compare them to the actual teams manually created by farm managers. Our simulator was developed using MASON [17], a discrete-event multi-agent simulation library and was introduced in previous work [7], where it was used to evaluate different methods of allocating tasks to workers within each team. The work here expands on this by bundling and sorting picking tasks. In our simulator, picking tasks are represented by patches (areas) of fruits that are ripe, as illustrated in Figure 1. The colour of the patches, represents the number of ripe fruits: red patches contain more ripe fruits than orange, which contain more than yellow, and green indicates low amounts of ripe fruits.

An agent in our system is a fruit picker and is defined by the tuple $p = \langle v, \ell, s_p, c \rangle$, where ℓ is the agent's initial location, v its navigation speed and s_p its picking speed (grams per step). When a picker has reached their capacity (c), they transport the picked fruit to a packing station. Tasks are allocated to pickers using SSI. A picking task is defined as an (x, y) location and a number of ripe fruits. The cost of a picking bid is the *duration* for the agent to complete all their previously assigned tasks plus the task being auctioned. The duration of a single picking task is the sum of three components: the time it takes the agent to navigate to their picking location; the time it takes to pick the ripe fruits; and, when c is reached, the time it takes to navigate to the packing station, drop off the fruits (currently a fixed value set to one timestep) and return to the patch.

Rather than a picker bidding on a single task, tasks can be *bundled* together by row and which aisle the picking is executed in, i.e. the row is split in half



(a) (b)

Fig. 1. Example of a commercial field: (a) within our simulator, and (b) a zoomed-in section highlighting areas within the polytunnel, namely a *row* where plants are growing, colour-coded according to ripeness, and *aisle*, the space between rows where pickers move. Each field has multiple horizontally and vertically adjacent polytunnels (the example field has 3×11 polytunnels) containing rows of crops, which are reached via aisles (the example polytunnels have 5 rows and 6 aisles). Each row contains two vertically adjacent fruit patches and can be any number of patches long (e.g. 10). See text for explanation of the colours.

lengthwise (for the example shown in Figure 1, each bundle will contain 10 tasks). This will decrease the distance travelled by agents and the likelihood of agents obstructing each other (since an agent will travel between fewer rows). When bidding on a bundled task, an agent will create bids for each of the independent picking tasks in a bundle, and the cost for the bundle will be the cost of the picker executing all its previously assigned tasks plus the tasks in the bundle.

To further optimise a picker's independent schedule, their tasks are sorted by (x, y) location. The agent will pick the row with the lowest x position (starting at the lowest y position) and then pick the second to lowest row, and so forth. This sorting occurs during the bidding process. The timings of all tasks proceeding the one being bid on are (provisionally) updated, and the cost of the bid is set to the end time of the last task. If the agent wins the task, the provisional task timings are retained.

4 Experiments

We received data from a commercial fruit farm during the 2021 picking season, covering 182 picking days and 30 fields. Each field contained one four types of soft fruit (strawberries, raspberries, blackberries or cherries). Our experiments assess our approach in the face of the three challenges introduced in Section 1:

1. Modelling from historic vs real-time and prognostic data:
   - *Historic:* The entire season of picking data was processed to create the worker model. Therefore, which worker is capable of picking each fruit is known. The default picking rank is only used when the picker has picked too few fruits to be able to calculate their picking speed.
   - *Live:* Only data recorded up to any given day is available, thus yield estimates are based on prognostic assessments by farm managers and worker models are based on picking records only up to the day before

the one being planned. This is the data that would be available if our system were running on a farm and managing labour on a daily basis.

2. Simulating actual vs proposed teams:
   - *Actual:* These are the results of using the teams created by farm managers (i.e. teams actually deployed), as produced by our simulator.
   - *Proposed:* These are the results of using the teams proposed by our methods (described in Section 3), as produced by the same simulator.
3. Clustering and determining default rank picking speed:
   - *Def_rank*: This is the default rank to use for modelling a worker when there is no information about that worker in the data set. Three values are compared: 3 (uses a mid-range picking speed), -1 (uses a picking speed lower than any worker with any experience) and $*$ (uses the average picking speed over all workers).
   - *N_clusters*: This is the number of clusters used for grouping workers. Two values are compared: 6 and $|W|$, where the latter is effectively "no clustering" since the number of clusters is equivalent to the number of workers. When the number of clusters is equal to $|W|$, the speed of the default rank is set to the average picking speed (denoted $*$ above); otherwise the default rank is either 3 or -1.

Two metrics are recorded to evaluate the affect of the different conditions and parameter settings listed above. These are:

- **execution time:** The amount of simulator time for each picking date, for each field. In other words, the amount of time that elapses between when the team arrives at the field and when the team finishes picking that field. As some workers could spend less time working than others, particularly if the workload is unevenly distributed, we also calculate staff time.
- **staff time:** The sum of the simulator time worked by all workers each day, for each field. This metric is a proxy for payroll costs.

Experiments were executed to evaluate the performance of our workforce management strategy, specifically as it relates to the choices of grouping workers into clusters and assigning a picking speed for workers for whom we have no data: *(def_rank=3, N_clusters=6)* versus *(def_rank=-1, N_clusters=6)* versus *(def_rank=*, N_clusters=*$|W|$*)*. Each experiment involved running our simulator under four conditions: *(Historic, Actual)*, *(Historic, Proposed)*, *(Live, Actual)* and *(Live, Proposed)*. For the *(Live, Proposed)* experiments, the estimated yield and list of available workers are used since, the actual yield and worker list would not be available when a schedule were created. For the *Historic* and *(Live, Actual)* experiments, the actual list of workers and actual yield are used. There is no stochasticity, and thus, for each setup, the simulation is ran once per date on each of the fields with a yield value.

5 Results

This section presents our experimental results. Numeric results are shown in Table 1. Plots are shown to compare the results; in all plots presented, error bars indicate ± 1 standard deviation. All samples are normally distributed, as confirmed using the Shapiro-Wilk test for normalcy [25]. We compare the performance metrics for the *actual* teams and our *proposed* teams for each of the three parameter settings discussed previously. Tests for significance between *actual* and *proposed* teams are performed using Student's t-test for two independent samples. Tests for significance amongst the three parameter settings (*Def_rank* and *N_clusters* combinations) are performed using one-way analysis of variance (ANOVA) with three samples. For all statistical tests, we use $p < 0.01$.

conditions		*parameters*		*number of*	*resulting metrics*	
data	*teams*	*def_rank*	*N_clusters*	*samples*	*execution time*	*staff time*
Hist	Actual	3	6	1019	*23,265* (13,146)	577,402 (353,091)
Hist	Actual	-1	6	1019	*23,265* (13,146)	577,402 (353,091)
Hist	Actual	*	$\lvert W \rvert$	1019	**22,879** (12,905)	**551,283** (324,557)
Hist	Prop	3	6	1019	**31,714** (10,423)	*522,211* (286,605)
Hist	Prop	-1	6	1019	**31,714** (10,423)	*522,211* (286,605)
Hist	Prop	*	$\lvert W \rvert$	1019	32,081 (12007)	**514,327** (279,039)
Live	Actual	3	6	1019	**23,594** (13,602)	**567,618** (340,717)
Live	Actual	-1	6	1019	*28,164* (23,912)	*621,310* (418,181)
Live	Actual	*	$\lvert W \rvert$	1019	24,817 (14,854)	580,586 (358,348)
Live	Prop	3	6	1024	***19,303*** (7,179)	***430,891*** (207,562)
Live	Prop	-1	6	1024	31,569 (12,942)	702,767 (394,499)
Live	Prop	*	$\lvert W \rvert$	1024	*23,610* (7,765)	*536,844* (283,541)

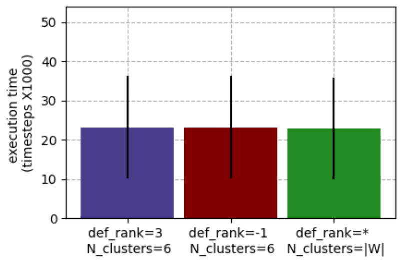
Table 1. Experimental results showing *mean* (and *standard deviation*) of execution time and staff time for all variables and conditions evaluated. Times are reported in terms of simulator time steps. The best values (shortest times) comparing parameters within one condition are highlighted in **bold**. The best values comparing between *actual* and *proposed* condition are highlighted in *italics*.

5.1 Historic Data

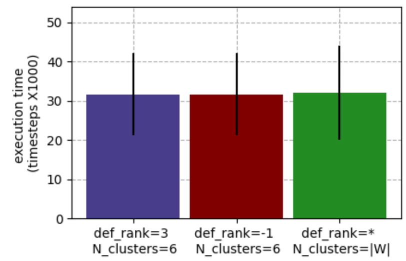
First, we look at results obtained using the *historic* data set. When comparing the *actual* teams with our *proposed* teams, our proposed teams fare better for staff time than execution time. The actual teams produced a shorter *execution time* than our proposed teams; the difference is statistically significant for all three parameter settings (T-test scores for each pair, in the order listed in Table 1: t=-16.07, p=0.000; t=-16.07, p=0.0000; t=-16.66, p=0.0000). However, our proposed teams resulted in a shorter *staff time* than the actual teams; again the difference is statistically significant for all three parameter settings (respectively: t=3.87, p=0.0001; t=3.87, p=0.0001; t=2.75, p=0.0060). **This is a positive result, since we are more concerned with reducing staff time than execution time.**

When comparing the three parameter settings, we find no statistically significant differences for either execution time (ANOVA scores for each triple within the Actual and Proposed times, respectively: F=0.297, p=0.7432; F=0.378, p= 0.6852) or staff time (respectively: F=1.958, p=0.1413; F=0.261, p=0.7700). These are illustrated in Figure 2.

Execution time:

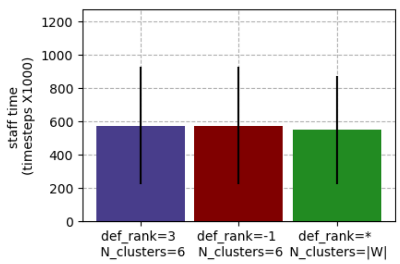


(a) Actual

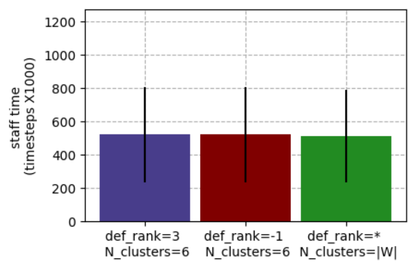


(b) Proposed

Staff time:



(c) Actual



(d) Proposed

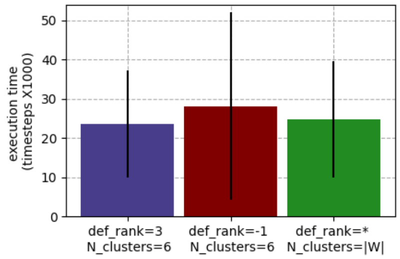
Fig. 2. Results for Actual versus Proposed teams using the *Historic* data set.

5.2 Live Data

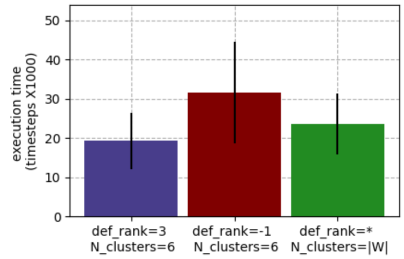
Second, we look at results obtained using the *live* data set. When comparing the *actual* teams with our *proposed* teams, **our proposed teams have better results for both execution and staff time for two of the three parameter settings**, excepting *(def_rank=-1, N_clusters=6)*. The results for the first two parameter settings for execution time are statistically significant, but not for the third *(def_rank=*, N_clusters=*$|W|$*)* (t-test scores, in the order listed in Table 1: t=8.919, p=0.0000; t=-4.004, p=0.0001; t=2.301, p=0.0214). **Results for all three parameter settings for staff time are statistically significant** (t=10.954, p=0.0000; t=-4.527, p=0.0000; t=3.058, p=0.0023), When comparing the three parameter settings, we find statistically significant differences for both execution time (Actual and Proposed times, respectively: F=17.4862, p=0.0000; F= 425.464, p=0.0000) and staff time (F=5.716, p=0.0033; F=206.488, p=0.0000, respectively).

However, for the two reasons described below, deciding which approach performs best is inconclusive. First, the default picking speed is inaccurate. As shown in Figure 3, for Proposed, there is a significant increase in time when the default rank is decreased from 3 to -1; for Actual, the difference is not significant. The proposed teams contained more pickers assigned to fruits they had no experience at picking than the actual teams. Thus, if the default rank (picking speed) is set too high, it will inflate the difference between the proposed teams

Execution time:

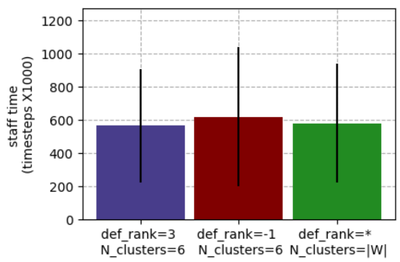


(a) Actual

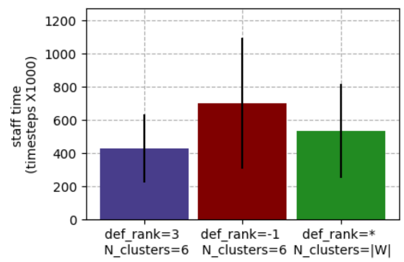


(b) Proposed

Staff time:



(c) Actual



(d) Proposed

Fig. 3. Results for Actual versus Proposed teams using the *Live* data set.

and the actual teams. The inverse is also true: the default rank could be set too low, causing the proposed teams to appear worse than they would actual be. Therefore, unless the default picking speed is not used, it is difficult to accurately evaluate results within simulation.

The second reason is due to inaccuracies in the estimated yield and the list of available workers. As mentioned in Section 4, the proposed teams (during the Live experiments) use the estimated yield and the worker availability lists since this is the information that will be available when the schedule is created. However, occasionally a field is estimated to be picked but is not actually picked, and vice versa. Therefore, the actual teams use the actual yield (since we do not have the deployed teams for fields that were not actually picked). This has resulted in the *(Live, Proposed)* experiment having a larger sample size than *(Live, Actual)*, as shown is Table 1. Further, some workers in the list of available workers may not actually work on certain days. Therefore, there will be differences in the resulting executing time and staff times caused by these inaccuracies.

6 Summary and Future Work

This paper has explored challenges affecting the evaluation and deployment of multi-agent task allocation method for managing the harvesting workforce. Our results have shown that when using a historical data set, our proposed teams produced significantly shorter *staff time* than the actual teams. Although the parameter setting *(Def_rank=*, N_clusters=*$|W|$) produced the best staff time results for both actual and proposed teams, the result is not statistically significant. When using a live data set, our proposed teams produced significantly shorter *execution time* and *staff time* than actual teams with two of the three parameter settings, the best being *(Def_rank=3, N_clusters=6)*. There are still questions about the validity of our method, given the number of aspects that are difficult to reproduce in a simulation. For the upcoming season, we are planning an experiment with a commercial farm in which we deploy our proposed teams in order to evaluate our method in a more realistic way. This will also give us data through which we can improve our simulator.

In future work, we will investigate evaluating further parameter settings and task allocation mechanisms, trialing the proposed team allocations at a commercial farm and evaluating our approach on a hybrid robotic-human workforce.

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