Towards Autonomous Task Allocation Using a Robot Team in a Food Factory

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***Abstract*—Scheduling of hygiene tasks in a food production environment is a complex challenge which is typically performed manually. Many factors must be considered during scheduling; this includes what training a hygiene operative (i.e. cleaning staff member) has undergone, the availability of hygiene operatives (holiday commitments, sick leave etc.) and the production constraints (how long does the oven take to cool, when does production begin again etc.). This paper seeks to apply multi-agent task allocation (MATA) to automate and optimise the process of allocating tasks to hygiene operatives. The intention is that this optimization module will form one part of a proposed larger system. that we propose to develop. A simulation has been created to function as a digital twin of a factory environment, allowing us to evaluate experimentally a variety of task allocation methodologies. Trialled methods include Round Robin (RR), Sequential Single Item (SSI) auctions, Lowest Bid and Least Contested Bid.**

***Index Terms*—multi-agent task allocation, food factory hygiene, simulation, multi-robot team**

I. Introduction

A large proportion of time is devoted to scheduling and performing hygiene tasks within a food factory environment. Cleaning and sanitizing equipment is fundamental to protecting public health by eliminating the spread of food-borne diseases. Staff retention of hygiene operatives is a challenge in itself due to often unpleasant, relentless work in uncomfortable and/or hazardous working environments, often conducted at unsociable hours.

To inform our approach, we conducted a survey of in-practise employees in the UK food industry. Survey participants included a mixture of Sustainability, Quality, Hygiene and Technical managers, as well as members of senior management teams within food businesses. The survey results informed us that generally hygiene operatives work in small, heterogeneous (only some operatives are trained to clean certain equipment) teams of less than five people. Half of respondents said that tasks were allocated on a flexible basis (rather than weekly or monthly rota).

The work presented here proposes that *Multi-Agent Task Allocation (MATA)* approaches can effectively automate the scheduling of cleaning tasks within a food production environment. A MATA approach is appropriate for situations where a set of tasks must be completed and there exist a team of actors to complete them. It is desirable for tasks to be allocated according to a given objective, such as minimising energy usage. There are many methodologies employed to solve MATA problems and the research presented here focuses on auction-based methodologies as used by [4] and strategies tailored to heterogeneous teams [6] applied to task allocation in a food factory environment [5]. Auctions have been proven to be a relatively simple, low (computational) cost method to achieving a close-to-optimal solution in relatively complex scenarios. Auction mechanisms scale well and can adapt dynamically to changes in the problem or scenario.

The simulation presented here draws on feedback from the survey and offers a first step towards providing a valid and appropriate digital twin of food hygiene teams working in factories.

II. Methodology

In order to explore optimisation of cleaning task allocation, we created a multi-agent based simulation using Mesa [1].

We consider the following task allocation mechanisms:

- *Round Robin* (RR) which involves the first task being assigned to the first agent, the second to the second agent etc.. The process then repeats if there are more tasks than agents until all the tasks have been assigned.
- *Sequential Single Item - Lowest Bid* (SSI-LB) whereby in each round of bidding, all unassigned tasks are bid on by all agents. The task with the lowest bid is assigned to the agent who places that bid.
- *Sequential Single Item - Least Contested Bid* (SSI-LCB) similar to SSI-LB, but the bid that is assigned is the one with the maximum difference between the lowest and second-lowest costing bids. If there is a tie between two or more tasks, then the task with the lowest costing bid is assigned.

Homogeneous agents are capable of cleaning all types of equipment ('tray washer', 'cheese grater', and 'bottle washer'). Heterogeneous agents have an 'expertise' for cleaning each type of equipment, shown by the following tuples: Agent 1 (1,1,1), Agent 2 (0,1,1), Agent 3 (1,0,1). For agents to bid for tasks, they must calculate the cost of a bid. The cost is the sum of three components: (1) the time taken to travel to the task (calculated using a *Jump Point Search (JPS)* algorithm [2], [3]); (2) the time taken to complete the task; and (3) the time taken to complete all of the tasks already within the agent's schedule. If an agent does not have expertise in carrying out a certain task, it cannot bid on that task.

Each piece of equipment has its own 'wash procedure', detailing the steps which must be undertaken by a hygiene operative to clean it. Each task within our simulation is defined as the complete 'wash procedure' for one piece of equipment.

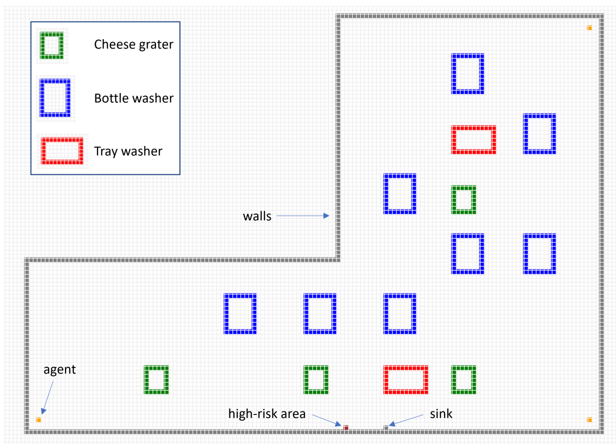


Fig. 1. Randomly generated factory layout.

III. Experiments

Figure 1 shows the simulation, within which agents are orange squares, a 'sink' as a grey square and a 'high-risk' as a brown square (some of the cleaning schedules involve transporting parts to the sink for washing or to the high-risk area).

Experimental conditions compared: *heterogenous* (agents have different values for expertise for different pieces of equipment) vs *homogeneous* (all agents have the same expertise, in all pieces of equipment) agents. Each experimental condition was executed 10 times, on 10 different factory layouts. For each run, we collected results for each method of allocation (RR, SSI-LB, SSI-LCB). For all runs we used 3 agents and the number of tasks ranged between 10 and 15 (according to the number of equipment generated by the simulation).

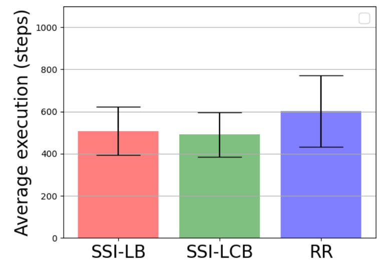
IV. Results

We analyse our results, shown in Figure 2, by looking at the average agent execution time in number of steps. Results gained using RR act as a baseline from which to evaluate other more effective methods.

We analysed the statistical significance of the results using the Kruskal-Wallis tests, and the associated H and p values are shown for each scenario. We use this test, rather than ANOVA test as the data for all scenarios has been calculated as not being of a normal distribution by the Shapiro-Wilk test.

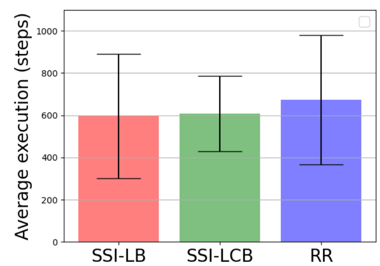
SSI-LB and SSI-LCB achieved a lower agent average execution time than for RR for both homogeneous and heterogeneous agents. Homogeneous teams perform faster than heterogeneous for each task allocation method (RR, SSI-LB, SSI-LCB), as expected as there are no constraints as

Homogeneous agents



(a) H=8.487, p=0.014

Heterogeneous agents



(b) H=1.1664, p=0.558

Fig. 2. Experimental results.

to which agent can conduct a particular task. Results for homogeneous agents are statistically significant, although are not for heterogeneous agents.

V. Conclusion

We propose to break up tasks into smaller chunks to achieve a greater granularity (currently the whole wash procedure for one piece of equipment is defined as a single task) to improve optimization. However, greater granularity in a real-world setting, when working with a human team, can cause extra complexity and have the potential for de-motivating workers by removing some of their autonomy. A practical balance will need to be found that enhances performance in terms of efficiency of execution and accuracy of cleaning while simultaneously not disengaging employees.

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