Towards the Application of Multi-Agent Task Allocation to Hygiene Tasks in the Food Production Industry

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Abstract. The food production industry faces the complex challenge of scheduling both production and hygiene tasks. These tasks are typically scheduled manually. However, due to the increasing costs of raw materials and the regulations factories must adhere to, inefficiencies can be costly. This paper presents the initial findings of a survey, conducted to learn more about the hygiene tasks within the industry and to inform research on how multi-agent task allocation (MATA) methodologies could automate and improve the scheduling of hygiene tasks. A simulation of a heterogeneous human workforce within a factory environment is presented. This work evaluates experimentally different strategies for applying market-based mechanisms, in particular Sequential Single Item (SSI) auctions, to the problem of allocation hygiene tasks to a heterogeneous workforce.

Keywords: Multi Agent Task Allocation · Food Hygiene · Multi Agent System · Agent Based Simulation.

1 Introduction

A large proportion of time is devoted to hygiene tasks within a food factory environment. Cleaning and sanitizing equipment is fundamental to protecting public health by eliminating the spread of foodborne diseases. If biofilms (thin but robust layers of a collection of microorganisms) are allowed to gain purchase, their resistance to detergents and disinfectants can cause serious issues. Due to the quantity of time devoted to cleaning, and the importance of these cleaning tasks, it is desirable to optimise cleaning operations.

The work presented here proposes that the application of a *Multi-Agent Task Allocation (MATA)* approach to the optimising the scheduling of cleaning tasks within a food production environment. To inform this 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 products they handle cover a broad range, including ambient products (products stored at ambient temperature such as dry and tinned food and food stored in glass jars), fresh salads, salmon processing, cheese, soft drinks, pasta, bread, sandwiches and microwaveable snacks. The intention of conducting the survey was to gain a more in-depth understanding of cleaning within the food industry, the procedures undertaken and the problems faced. We wanted to understand the nature of the cleaning teams and the mechanisms for allocating cleaning tasks to cleaning operatives who conduct cleaning tasks. We were also interested in understanding which tasks are particularly disliked by or dangerous to operatives. An overview of the survey results told us that generally hygiene operatives work in small teams of less than five, and most teams are heterogeneous (only some operatives are trained to carry out certain cleaning tasks). Half of respondents said that tasks were allocated on a flexible basis (rather than weekly or monthly rota). It appears that there is potentially a lack of formalisation of task allocation, with scope for improvements in efficiency.

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; this may be to minimise energy usage, or to maximise reward. There are many methodologies employed to solve MATA problems and the research presented here focuses on auction-based methodologies similar to [10] and strategies tailored to heterogeneous teams [22]. 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. Here we propose MATA as an approach to job scheduling for hygiene tasks within the food production industry, introducing this domain to the multi-agent systems community as a compelling and complex environment for research and development. Two contributions are presented: first, the results of our survey, which illustrates specific features of this task domain; and second, a simulation that demonstrates these features. The simulation 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, and as a platform for future experimentation with task allocation methodologies.

This paper is structured as follows: Section 2 gives background information on hygiene in the food industry. Section 3 details our survey results. Section 4 provides the methodology used for experimentation within the simulation. Section 5 explains our experiment design and Section 6 details the results obtained through experimentation. Section 7 closes with a summary and overview of next steps.

2 Background

Food businesses follow standard hygiene protocols and processes. This section provides an introduction to these and Multi-Agent Task Allocation (MATA) methods, which could improve the efficiency of how these processes are scheduled.

2.1 Food Safety and Hazard Analysis and Critical Control Point (HACCP)

In the UK (where this research was conducted), all food businesses must, by law, have a food safety management plan based on Hazard Analysis and Critical Control Point (HACCP) principles. The plan keeps food produced safe from biological, chemical and physical food safety hazards [1]. The plan must identify hazards and methods for controlling these hazards, as well as setting limits and putting things right if a problem is detected. Monitoring of the plan must be maintained and records kept.

Cleaning falls under "preparatory stage A", a *prerequisite* for HACCP [3] as the basic hygiene measures that should be put in place within a business prior to undertaking a HACCP study. There is a tendency, due to cleaning being a prerequisite and not a core component of the HACCP, for cleaning processes to be less formalised.

Two main practices for cleaning production equipment exist: *cleaning-in-place (CIP)* involves equipment being cleaned by an automated system that runs cleaning chemicals through the equipment without the need for dismantling it, and *cleaning-out-of-place (COP)* where cleaning operatives dismantle equipment before cleaning by hand, e.g. using hand-held water jets. *Open Plant Cleaning (OPC)* involves cleaning walls, ceilings, floors and drain gullies etc. Guided by our survey results (as detailed in Section 3), we focus here on COP processes.

2.2 COP Process Steps

In essence, COP processes are simple, with the main backbone following these steps: pre-rinse; wash; post-cleaning rinse; disinfection and final rinse [15].

- **Pre-rinse:** use of water to remove coarse debris and food residues from the surface of equipment. Factors include the type of soiling, applied force necessary to remove the soil and the rinse water temperature.
- **Wash:** use of detergent to scour or scrub equipment in order to remove odors, residual food or other extraneous materials. Critical factors include surface finish, detergent type, concentration and exposure time.
- **Post-cleaning rinse:** for preventing the re-deposit of food soils or foreign matter onto the cleaned surface.
- **Disinfection:** the reduction of undesirable microorganisms to specified and acceptable levels. Identification and characterization of expected microorganisms must be conducted in order to properly target them—inability to do this may include loss in product shelf-life, or life-threatening foodborne illness outbreaks.
- **Final rinse:** removal of the chemicals used in disinfecting in the previous step, due to their toxicity. Many governments globally have maximum residue levels (MRLs) specified for such chemicals.

2.3 Adaption of MATA Methodologies to Food Factory Hygiene Tasks

Our work explores the application of multi-agent and multi-agent task allocation (*MATA*) strategies to the problem of allocating the hygiene tasks performed within the food factories to members of the cleaning teams. In particular, we focus on auction-based mechanisms, which are a popular technique within the MATA and multi-robot task allocation (MRTA) literature. As described by [8, 10, 12, 13, 20], 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).

The approach explored here draws specifically on two prior works in the literature: [10], where auctions are used to efficiently manage a human fruit harvesting workforce, and [22], where improvements to standard auction mechanisms have been made to tailor allocation to heterogeneous robot teams. In [10], tasks are allocated to *pickers*, who pick the ripe fruits, and *runners*, who collect the fruit from the pickers and transport it to a packing station. *Round Robin*, *Ordered Single Item* and *Sequential Single Item* methods are employed.

Round Robin (RR) differs from standard auction mechanisms in that only the winner determination phase occurs. The winner is assigned by cycling though ordered lists of agents and tasks, assigning each agent a task in turn. The process concludes when all tasks have been assigned. 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). Nevertheless, the cost of a task is not considered, synergies between tasks are not exploited and the result is highly dependent on the order in which tasks and agents are matched. As a result, RR alone can result in inefficient task allocations.

In the Sequential Single-Item (SSI) [14], all unassigned tasks are announced to the agents, who place bids on all tasks. The auction manager determines the winner by picking the bidder with the 'best' bid for any task (where the definition of 'best' is domain dependent). The auction repeats in rounds until all tasks have been allocated. SSI is fast (the auction runs in polynomial time in the worst case) and efficient, while also being able to produce an allocation that is close to or within a guaranteed factor away from optimal [14]. SSI has been a popular choice for multi-robot task allocation, and many variants have been studied (e.g. [11, 16–19, 21, 22]).

The work of [22] seeks to improve the performance of SSI when used to assign tasks to heterogeneous robot teams, minimising energy usage and time required to complete all tasks within an experimental domain. The authors state that their algorithms provided consistent and significant improvements for both objectives for a number of scenarios, up to 20% improvement. They developed methods for changing the order in which tasks are allocated to avoid the 'hill-climbing' (building a path in one direction before later being required to complete a task in a different direction) behaviour that SSI can generate. They seek to first allocate tasks that have low levels of competition by employing the *least contested bid*. In addition, using a 'relative expertise' parameter, agents can determine whether or not to bid on a particular task (based on whether they have a relatively high expertise or not).

Other methods documented in relevant research consider the allocation problem as a flow-shop model, as in [7]—an optimization problem whereby optimal job scheduling is desired for n jobs of varying processing times on m machines of varying processing power. Biologically-inspired solutions to these types of problems include *Ant Colony Optimization (ACO)* and *Modified Genetic Algorithm (MGA)* for optimization. The work of [6] uses *Mixed-Integer Linear Programming (MILP)* to schedule product runs on a number of different production lines. While we focus here on auctions, our future work may consider these, and other, methods.

3 Survey Results

Our survey was administered to volunteers recruited from a pool of in-practice professionals working in the UK food industry. Results are presented from 10 respondents. We provide the survey questions asked to participants and analysis of the responses. Where questions were presented as multiple choice, analysis has been given as the percentage of participants giving each of the possible answers. Where questions required a text description, we have conducted thematic analysis to understand the underlying themes [4].

1. What is your role within the business?
   - *Technical Manager, Sustainability Manager, Quality Manager, QA Technologist, Site Quality Manager, Site Hygiene Manager, Head of Technical, QA Manager, Senior Management, Technical Manager*
2. What does your business manufacture?
   - *Ambient products, vertically farmed salad, salmon processing, cheese, soft drinks, pre-packed salad mixes and whole-head salad vegetables, pasta, packers, sandwiches and microwaveable snacks, sourdough*
3. What determines when cleaning occurs (clean-as-you-go, in-between production runs, deep cleaning etc)?
   - *All responses describe a variety of combinations including clean-as-you-go, periodic deep clean, shut downs, between product types*
4. Do employees have different skills for cleaning particular equipment?
   - *Yes, individuals often have different training to carry out cleaning of different equipment (60%); no, all members of the team are trained to carry out all cleaning tasks (40%)*
5. Who allocates cleaning tasks?
   - *Team leader (60%); Hygiene manager (30%); Other (10%)*
6. How are tasks allocated?

  - *Flexible each day/shift (50%); Other (30%); Weekly rota (20%)*
7. What data or metrics are collected regarding hygiene?
   - *Strong themes were swabbing—micro and instant ATP (detection of adenosine triphosphate, a molecule found in all living things); also mentioned were taking water samples, visual inspections for hygiene audits, staff attendance, production downtime, TVC (Total Viable Counts of microorganisms)/Listeria/Pseudomonas swab pass rates, chemical concentrations and pH levels*
8. Do any data or metrics inform cleaning task allocation?
   - *Mainly participants answered no, although other answers were based on determining the level of the frequency of cleaning, swab results and sign off sheets*
9. Do employees work together when carrying out cleaning of the ceilings, walls, floor and exterior surfaces of equipment?
   - *Small teams of less than 5 people (70%); Individual employees work alone on a task (20%); Other (10%)*
10. How is the team organised during the task?
    - *Everyone knows exactly which sub-tasks they will complete (50%); not structured—anyone can do any sub-task (37.5%); Other (12.5%)*
11. Are there factors that could delay the cleaning of ceilings, walls, floor and exterior surfaces of equipment?
    - *Almost all responses mentioned access to rooms and equipment, especially at high levels or if cables and other equipment blocks the way. Also mentioned was production seasons or growing cycles (for fresh produce).*
12. What are the most time consuming aspects of the cleaning schedule?
    - *Manual cleaning; taking equipment apart; removing gross debris and organising which staff can do what.*
13. What are the most time consuming aspects of the hygiene monitoring schedule?
    - *Swabbing and waiting for results. Other responses mentioned monthly hygiene audits and water sampling.*
14. What aspects of the cleaning and monitoring schedules are inefficient?
    - *A variety of responses without one clear theme. Several participants responded 'not sure' or 'nothing', and one responded 'lacking a clear plan for who does what and when'.*
15. What are the main hazards to employees during cleaning?
    - *Exposure to harsh cleaning chemicals and risk of slips and trips were the main themes and other responses included using sharp equipment, working at height or in confined spaces.*
16. Which jobs do employees dislike or feel uncomfortable doing?
    - *Working at height, working in cold, confined spaces, or generally cleaning is disliked.*
17. Which jobs do employees tend to make mistakes and why?
    - *Employees can miss hard to reach areas, trap points or undersides and interiors of surfaces. Other responses mentioned lack of understanding of training, rushing and strict time pressures with the possibility for cross-contamination between not-cleaned and cleaned areas.*

18. Which parts of the factory are the most demanding for maintaining hygiene levels and why?
    – *High care areas due to a lot of equipment (with poor hygienic design) being present in a small floor space. Hard to reach areas and confined spaces like a spiral freezer were also a challenge.*

We understand from responses that allocation of cleaning tasks can be carried out in a flexible manner and generally, data is not used to guide allocation. Operatives usually work in small, heterogeneous teams and a variety of different cleaning practices occur (clean-as-you-go, in-between production/product types, deep clean and shut-downs). Generally the team knows which tasks they will complete, but almost 38% of the time, task allocation is not structured.

Regarding disliked and dangerous tasks, generally tasks at heights, in cold or constricted areas are disliked and hazardous, in addition to exposure to cleaning chemicals and danger from sharp equipment. Dismantling equipment and manual cleaning are time consuming and, generally, operatives do not enjoy cleaning. Future introduction of robots into cleaning teams has the potential to reduce human exposure to cleaning chemicals and to dangerous conditions. The methodology presented here applies to human workforces of today but also has relevance to hybrid human-robot workforces of the future.

4 Methodology

In order to explore optimisation of cleaning task allocation, a multi-agent based simulation has been created using Mesa [2]. The simulation employs a variety of auction mechanisms to allocate cleaning tasks. Definition of cleaning tasks is based on the five clean-out-of-place (COP) process steps (detailed in Section 2.2).

Each COP step for each piece of equipment is defined as one task within the simulation. Initially we assume that each piece of equipment will need a 'pre-rinse' according to step 1 of the COP process.

4.1 Agents

Each agent has a specified 'expertise' for cleaning each type of equipment ('tray washer', 'cheese grater', and 'bottle washer'). Within the simulation, it is possible to vary the agent start positions.

4.2 Task Allocation Mechanisms

For the work presented here, we consider the following mechanisms:

– *Round Robin* (RR) to be used as a baseline for other mechanisms. This involves the first task being assigned to the first agent, the second to the second agent and so forth until each agent has been assigned one task or the list of tasks has been exhausted. If there are more tasks than agents, then the process repeats 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.

4.3 Allocation of Cleaning Tasks

For pre-rinse tasks, each task is defined as a list of the perimeter squares for one piece of equipment. In order for agents to bid for tasks, they must calculate the minimum distance to any of the grid squares contained within that task. The bid is made up of the sum of the minimum travel time to the task (calculated using a *Jump Point Search (JPS)* algorithm [5, 9]), the time taken to complete the task (to travel the perimeter of the equipment) as well as 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—therefore agents bid only on tasks which they are able to complete.

4.4 Execution of Simulation

During execution of agent schedules within the simulation visual environment, operatives move to pieces of equipment in the order in which they appear in their schedules and travel around the perimeter of each equipment. They move through the following states: 'awaiting task assignment', 'waiting to start task', 'navigating', 'cleaning', 'finished task', finally to 'finished all tasks' if they have completed their final task, or back to 'waiting to start task' if there are more tasks to complete.

5 Experiments

Within the simulation, a grid world environment has been created. The dimensions of the room are based on a real pilot plant. Within the plant environment, a randomly generated layout of factory equipment is activated each time a new experiment is begun. Figure 1 shows one example of a randomly generated equipment layout. The amount of equipment, between 15 and 20 pieces, is generated at randomly selected locations (based on a grid structure). Sizes of surfaces are generated, between 5 and 10 grid squares for each piece of equipment. Equipment is randomly allocated as being a 'tray washer' (shown in green), 'cheese grater' (shown in red), or 'bottle washer' (shown in blue), each with their own COP requirements. Three agents are shown as orange grid squares.

We developed a scheduler to run a number of experiments (we used 10 experiments for this work). For each experiment, the same factory layout was used

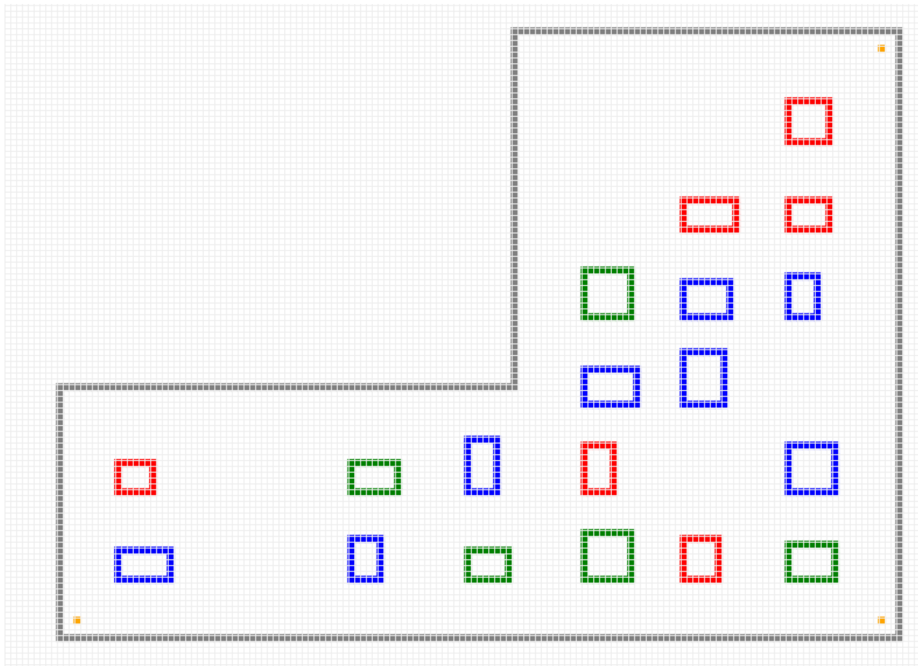


Fig. 1: One configuration of the randomly generated factory layout.

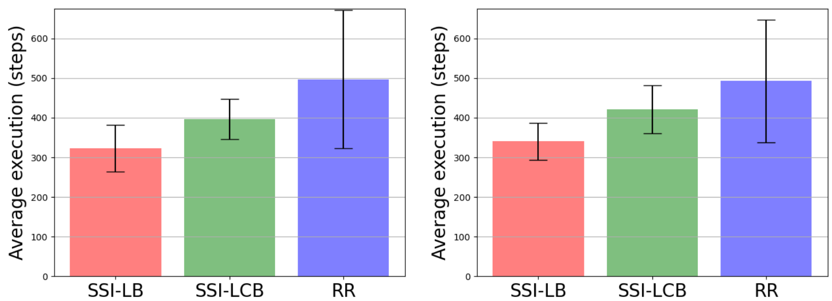
to compute average agent execution time of all tasks for each of the three mechanisms (RR, SSI-LB and SSI-LCB). We define average agent execution time as the average time taken for all agents to complete all of the allocated tasks within their schedule. Once an experiment had been performed, a new factory layout was generated and the process repeated until the 10 experiments had been completed.

Experimental conditions compared: *heterogenous* (agents with different values for expertise for different pieces of equipment) vs *homogeneous* (all agents have expertise in all pieces of equipment) agents and for agent starting positions *together* (in the bottom left hand corner of the simulated environment) vs *spread out* at the corners of the factory. Thus we had $\{het|hom\} \times \{tog|spread\} = 4$ combinations of configuration parameters. Each was run 10 times, on different factory layouts, so the results are analysed over 40 runs. For each of the 40 runs, 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 15 and 20 (according to the number of equipment generated by the simulation).

6 Results

We analyse our results by looking at the average agent execution time for each of our four scenarios. By optimising performance, we look to minimise the average agent execution time. Results gained using RR act as a baseline from which to evaluate other more effective methods. Fig. 2 shows results for heterogeneous and homogeneous agents. We analysed the statistical significance of the results using the Kruskal-Wallis tests and associated H and p values are shown for all scenarios. We use the Kruskal-Wallis test, rather than an Anova t test as the data for all scenarios has been calculated as not being of a normal distribution by the Shapiro-Wilk test.

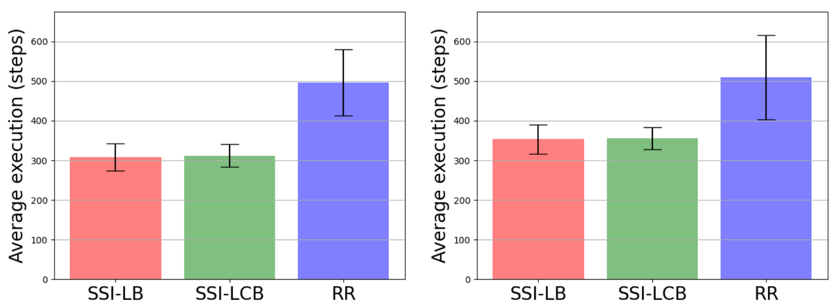
Heterogeneous agents



(a) Different start locations
H=26.46, p=0.00000

(b) Same start locations
H=30.04, p=0.00000

Homogeneous agents



(c) Different start locations
H=58.80, p=0.00000

(d) Same start locations
H=42.54, p=0.00000

Fig. 2: Average agent task completion time for heterogeneous and homogeneous agents.

For all four scenarios, SSI-LB achieved a lower average execution time than RR and SSI-LCB; the difference is statistically significant. Scenarios where agents started at spread out locations achieved lower average execution time than when agents started together. For both SSI-LB and SSI-LCB, homogeneous agents achieved a lower average execution time than for heterogeneous agents. Average execution times for SSI-LB and SSI-LCB were more similar for homogeneous agents than for heterogeneous agents.

7 Summary

This paper made steps towards investigating the application of market-based task-allocation mechanisms to the problem of allocating hygiene tasks to operatives in a food factory. A survey is presented and results analysed, giving a greater understanding of the sector. The survey helped to shape the creation of a simulation both to act as a valid and appropriate digital twin and to provide a platform in which to carry out experimentation of task allocation methodologies. Sample results using this simulation were shared.

Future work will look to build upon the list of tasks to include all stages of COP processes for each type of equipment, using relevant cleaning schedules. In order to do this, we must look at task durations (which may vary with expertise) as well as the cleaning equipment required. This will lead us to build different types of tasks into the simulation, such as 'collect detergent solution from store', or 'bring hose to another employee' or even 'clean the cleaning equipment'. An understanding of task dependencies will be required at this stage. We will look to investigate non-binary values for expertise for agents. Another avenue that we plan to explore is hygiene monitoring which could result in tasks needing to be repeated if cleaning has failed inspection. The complexity of these scheduling challenges makes this domain a compelling area for employing MATA.

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