On Multi-Agent Coordination of Agri-Robot Fleets

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Abstract. The need for sustainable agriculture has led to the recent introduction of Agriculture Mobile Robots (AMRs) and Precision Agriculture (PA) techniques designed to make the practice of farming more accurate, better controlled and more environmentally sound. To date, AMR research has focused on a single robot and its agriculture-specific capabilities. Very little work has been done with respect to efficient and scalable real-time agricultural vehicles in general, and more specifically with respect to AMR fleet coordination (FC). This is especially the case when considering overall fleet performance, as well as tactical and operational real-time vehicles that can accommodate implementation and crop cultivation constraints. This topic is of the utmost importance in the case of commercial agriculture where major conglomerates with large and heterogeneous agriculture vehicle fleets could operate on huge land areas to effect precision farming. In this paper, we discuss distributed and decentralized multi-agent coordination models applicable in AMR fleet coordination. Dynamic coordination approaches are reviewed focusing on the application of the multi-index assignment problem and the classical assignment problem. We discuss some open issues and research opportunities in this context.

1 Introduction

The goal of sustainable agriculture is to meet society's need for food and textiles without compromising the ability of future generations to meet their own needs [53]. This requires the optimisation of input resources (e.g. fuel, water, fertilisers) to maximise productivity, quality and yield and minimise waste, costs and diseases while considering ecological factors by minimising application of pesticides. Developments in sustainable agriculture have led to the recent introduction of *Agricultural Mobile Robots*, or *agri-robots*, and *Precision Agriculture*, designed to make the practice of farming more efficient, accurate, controlled and environmentally friendly [26] (e.g. reducing greenhouse gasses, conserving water, minimising pesticides and protecting soil).

To date, agri-robotics research has focused on single robot systems and mostly on functional challenges: navigation, control, sensing, image processing, platform stability, terrain handling and hardware/software infrastructure (e.g. balancing computation between *edge* and *cloud* architectures). Little work has examined efficient, scalable, real-time, dynamic fleet coordination, considering tactical and operational agricultural setting constraints. This topic is of the utmost importance in commercial agriculture, where major conglomerates could operate huge land areas with precision farming.

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Fleet coordination systems are commonly used to coordinate mobility and delivery services in a wide variety of domains. Their application in the coordination of large agriculture fleets is less complex than in road traffic, but still highly challenging since "traffic" in the agriculture field emerges from the interaction of multiple collaborative decision makers. In practice, fleets are conventionally coordinated dividing an area of interest in sectors, each one assigned to a single human controller. The optimisation of the tractors and tractor-implement combinations[4] is still left to a human operator. Planning and scheduling of agri-robot and tractor tasks, paths and related tractor-implement configurations, drivers and controllers is still left to human planners. Such a segmented myopic view is one source of loss of efficiency for the overall system. Fully autonomous farming, with multiple robots coordinating simultaneously with one another in the same farm, is still an open challenge.

Our focus is on scalable and efficient multi-agent models, particularly *dynamic task assignment (DTA)* approaches applicable to heterogeneous agriculture vehicle fleets operating on large-scale farms, potentially managing multiple crops. The main question is: How can these technologies improve the efficiency and autonomy of agriculture machinery fleets while decreasing their cost and dependence on humans?

This paper is intended for researchers in distributed optimisation and multi-agent coordination, to highlight the possibilities of integrating these two fields with application in the real-world domain of sustainable agriculture. We also address researchers in agriculture, by demonstrating the added value of the application of combinatorial optimisation and multi-agent systems technologies to everyday problems faced in agricultural settings. The content may be relevant for researchers or practitioners who wish to learn more about and/or engage with problems in this domain. In Section 2, we describe the background and context of farming with agriculture machinery. Section 3 presents main features of multi-agent architectures which are applicable in this context. In Section 4, we introduce the dynamic agriculture vehicle fleet coordination problem. Section 5 describes state-of-the-art optimisation models and algorithms for multi-agent agriculture fleet coordination. Finally, we discuss some open issues and conclude the paper with future work in Section 6.

2 Autonomy of agriculture vehicles

In this section, we briefly describe the agriculture domain and then define agri-robot autonomy within this context.

Tractors are farm vehicles that provide traction powered by slow speed, high torque engines to mechanise agricultural tasks. These tasks include, among others, pulling or pushing of agricultural implements or trailers, tillage, plowing, disking, harrowing and planting. Agricultural tools, or *implements*, include: irrigation machinery (e.g.

[4] For example, a tractor pulling a tiller

central pivot irrigation systems, pumps, sprinklers), soil cultivation implements (e.g. trowels, spikes, harrows, plows, tillers), planting machines (e.g. drills, seeders, spreaders), and harvesting machines (e.g. trailers, diggers, pickers). These implements may be towed behind or mounted on the tractor. The tractor may provide power for the implement, if required. This flexibility means that a farmer can purchase a tractor and a number of attachments (implements) without needing to acquire and maintain multiple different types of specialised farm vehicles. In general, implement mounting, attaching and removal are still not suitable for automation but can be performed by human operators in a matter of minutes.

According to the levels of vehicle autonomy described in [59], we focus on: tractors with driver assistance (level 1), semi-automated tractors (level 2–partial automation), driverless remotely supervised tractors (level 3–conditional automation), driverless fully autonomous tractors (level 4–high automation) and complete automation (level 5). At the driver assistance level (1), there is no automated decision-making. Operational decisions are taken by a human driver (e.g. steering and path following), while a fleet controller makes tactical decisions about the vehicle(s) (e.g. path and task planning), supervises the performance of the whole fleet and performs tractor-field assignment. In the case of a semi-automated tractor (level 2), the driver's only is to supervise the vehicle and handle emergencies. Driverless remotely supervised tractors (level 3) operate without a human inside the tractor itself, but still under supervision of a human controller positioned at a control station. These tractors use *vehicle-to-vehicle (V2V)* and *vehicle-to-infrastructure (V2I)* communication for receiving driving instructions from a remote human controller.

A driverless fully autonomous tractor (level 4) is capable of independently performing its assigned task while tracking its GPS position, controlling its speed and sensing and avoiding obstacles in front of it. The environment of an assigned task has to be deterministic (the task is defined before it starts and the next state of the environment is determined by the current state and the actions performed, e.g. following a predetermined path on a field) [15]. Any delay in decision-making for the action choice must be as small as possible, preferably instantaneous without hesitation or time-consuming calculations (e.g. changing the steering angle when necessary). Sensor technologies improve safety by detecting unforeseen obstacles while reactive behaviours are for rapid response. Currently, the majority of fully autonomous tractors navigate using lasers that bounce signals off several mobile transponders located around the field.

Highly automated agriculture vehicles (level 5) are mostly applied for weed control (e.g. [37]), seeding (e.g. [2, 8]), harvesting (e.g. [66, 71]), environmental monitoring (e.g. [36, 51] and soil analysis (e.g. [17, 68]). Completely autonomous agriculture systems are expected to be realised in the future [50].

Autonomous tractors and agri-robots may also work in tandem with traditional machines whose drivers supervise their activities. We limit our discussion to autonomous vehicles that can be programmed, can interact with each other and with humans in real time.

3 Decentralizing coordination for agri-robot fleets

Fleet Coordination (FC) systems are commonly used to coordinate mobility and delivery services in a wide variety of domains. However, traditional top-down centralised control architectures become a bottleneck in open and dynamic environments such as agriculture, where scalability, proactiveness and autonomy are key factors for success. Conventional FC systems require a control centre (with human operators) that monitors and coordinates each of the fleet's robots, tracks their performance in real time, and responds to contingencies. The higher the fleet's operational costs, the more importance is given to the fleet's coordination. Fleets are conventionally coordinated by dividing an area of interest into sectors, each one assigned to a single human controller. Such a segmented myopic view is a source of loss of efficiency for the overall system.

Our aim is to shift the current centralised fleet coordination paradigm toward distributed FC systems for agri-robots. Fleet owners, farmers, agriculture vehicles, operators and controllers may each be modelled as a *rational* agent, each with its own local constraints and decision-making objectives that should be optimised (e.g. [11, 60]). These objectives generally include finding a minimum cost matching of agents, implements and tasks, applied to a set of time periods. In this *multi-agent dynamic task allocation* context, available vehicles, drivers and implements should be (re-) assigned to each other and to pending tasks as new tasks appear.

Generally, coordination may be defined as the process of organising people or groups so that they work together properly and well [14]. By the coordination of agriculture vehicle fleets, we refer to the organisation and management of decision-making within the agriculture fleet with the aim of improving given key performance indicator(s) of a fleet's task allocation.

The topics of coordination and task allocation are the object of studies in multiple disciplines—e.g. operations research, economics and computer science. The corresponding definitions and related concepts may vary based on the specific discipline at hand. In our survey, and in the following, we focus on the specific issues of dynamic task allocation and distributed vs decentralised coordination. Task allocation problems in agriculture vehicle fleets consider providers of farming services (fleet owner(s)), drivers, vehicles, and their customers (farm owners) and thus all of them may be considered active participants in the farming process.

Based on the ownership of the fleet, its structure, and the level of decentralising coordination that we want to achieve in the fleet task allocation, we can design:

- **a centralised coordination model**, where the task allocation problem is solved in a single block by only one decision-maker (e.g. a single entity) having total control over and complete information about the vehicle fleet;
- **a distributed coordination model**, in the context of small farmers with only one vehicle fleet owner, where the global task allocation problem is decomposed such that each farmer is represented by an autonomous decision maker (agent) that may solve its own subproblem only using its own local decision variables and parameters. The allocation of a limited number of agriculture machinery (global constraints) is achieved through the interaction between competing farmer agents and the vehicle fleet owner (a single autonomous agent) having all the fleet information available. Farmer agents that compete for resources are not willing to disclose their complete information but will share a part of it if it facilitates achieving their local objectives. The vehicle fleet owner agent is responsible for achieving globally efficient resource allocation by interacting with farmer agents usually through an auction. The problem decomposition here is done to gain computational efficiency since farmer agents can compute their bids in parallel. However, the resource allocation decisions are still made by a single decision maker (vehicle fleet owner) with the requirement on synchronous bidding of farmer agents (e.g. [21, 22, 69]); or
- **a decentralised coordination model**, which further decentralises the distributed model by allowing for multiple resource (vehicle)

owner agents, multiple competing farmer and/or agents requesting the farming service, and asynchrony in decision-making. Each farmer and resource owner agent has access only to its local information, with no global information available. Farmer agents are responsible of the execution of a set of (possibly overlapping) field tasks. The objective for the subset of tasks belonging to an individual farmer agent is to perform them at a minimal overall cost, which reflects in specific task constraints. The individual task allocation cost here is less important than the overall cost of a competitive farmer agent. A set of tasks belonging to each farmer agent competes with the sets of tasks of other farmers for the fleet's vehicles held by multiple resource owners. Similarly, if the vehicles are owned by multiple fleet owners, then each vehicle agent should coordinate the allocation of its tasks with other vehicle agents of the fleet such that the overall operational costs of the fleet owner in performing the allocated tasks are minimised. The decisions specifying these interactions emerge from local information. Fairness in resource allocation here plays a major role. The same as in the distributed model, a competitive agent is not willing to disclose its complete information but will share a part of it if it facilitates achieving its local objective. Resource allocation here is achieved by the means of a decentralised protocol.

Generally speaking, coordination is distributed when complex behaviour within a system does not emerge due to the control of a single agent (e.g. the system owner), but rather through interactions and communication between individual agents, each operating on local information. This form of control is typically known as *distributed control*, that is, control where each agent is equally responsible for contributing to the global, complex behaviour by acting rationally and collaboratively with one another based on their local information. Agents are implicitly aware of the interaction rules (e.g. *norms*) through mechanisms that are based on the agent's interaction with other agents and the environment. The system behaviour is then an emergent property of distributed coordination mechanisms (algorithms) that act upon agents, rather than the result of a control mechanism of one centralised system owner.

In *decentralised* algorithms, no global clock is assumed, no agent has complete information about the system's state, every agent makes its own decisions based only on its local information and failure of one agent does not prevent the system to continue running. An example is BitCoin: instead of one central server owned and operated by a single entity, Bitcoin's ledger is distributed across the globe, making it impossible to shut down, break in or hack, as there is no single central bottleneck of the system.

We note here the main differences between *distributed* and *decentralised* coordination models. Distributed coordination relies on both local and shared (global) parameters and variables; decentralised coordination only has access to local information. *Local* parameters and variables are *private* (known only to the agent who holds them), whereas *global* parameters and variables are *public* and shared among two or more agents—potentially among all the agents in the system. If we assume selfish agents, in the case of distributed coordination, resource owners can manipulate these parameters and variables or deceive agents in communicating their values to influence the individual decision making of each one of them and thus obtain the behaviour of the system the resource owner wants. This can be prevented by ensuring individual agents have access to non-obsolete and truthful information—using e.g. blockchain technology. In this case, reaching the globally optimal solution with a high-quality solution guarantee is possible, contrary to the decentralised coordination case in which, due to the lack of global information, quality of solution guarantees generally do not exist. Further, due to the lack of global non-obsolete and truthful information, in general, solution approaches for decentralised coordination concentrate on finding a feasible (admissible) solution without quality of solution guarantees. In contrast with the distributed case most often studied in the operations research field, where the emphasis is on the method's optimality gap, decentralised coordination methods are mostly approximate heuristics-based methods without quality of solution guarantees but with proven completeness, soundness and termination—hence most appropriate for deployment in real-world, dynamic and messy environments such as agricultural robotics.

4 Dynamic coordination of agri-robot fleets

Planning and scheduling of different stages of cultivation for each crop are based on agri-food production goals and agronomic needs. These are typically determined by tables for technical itineraries, which describe the entire cycle of crop cultivation processes throughout the year. For example, for the cultivation of maize in Spain, the scheduling of tasks is: deep ploughing in January; stone removal in February and March; harrowing, seeding and fertilisation, fertilising inserting, irrigation system, maintaining herbicide application in April and May; preseeding irrigation, and seeding and soil disinfection in June, etc. [61]. Technical itinerary tables also include scheduling of labourers for each month, required equipment and labour (driver/labourer), yield in hours per hectare of equipment and labour, and raw material (units per hectare).

In this paper, we focus on large agriculture conglomerates that grow multiple crops simultaneously. This means that crops with different needs will share the same agriculture resources and a heterogeneous vehicle fleet. Each one of these crops requires labours that need specific equipment for their implementation, usually a certain type of tractor and a compatible implement with specific characteristics. For example, for deep ploughing, we need a tractor and a chisel; for stone removing, a tractor and a trailer.

The matching between tractors and implements is done depending on the compatibility and the characteristics of the tractors and the implements at hand, and the terrain to be cultivated. In the case of traditional tractors, we also need to include drivers, their availability and specialisation(s) in the matching problem.

Fertilisers, herbicides, fungicides and growth regulators are typically applied at specific stages of plant development in quantities and frequencies that can depend dynamically on field conditions. These conditions may vary from one part of the field to another due to differences in crop development, soil characteristics (e.g. inclination, chemical structure, etc.), varying microclimate (e.g. local sun exposure, temperature, humidity), prevalence of pests (e.g. insects) and weeds and plant disease development. Thus, tasks have to be planned locally based on these differences and may vary from one field location to another with given short-time weather windows in which they have to be performed. Potentially, they may extend across a 24-hour working day.

The matching is done based on the list of labours to perform in the fields, field and weather conditions, availability of individual actors, etc. For each vehicle, a schedule is given throughout the workday in terms of a route to follow and the plan of labours to do in the field on this route, as well as the remounting of implements when necessary. Work breaks are preplanned and incorporated into the schedule.

Planning and scheduling of these tasks should be performed considering available labour, machinery, and raw material, minimising the overall time of operations and costs, optimising the amount to produce (yield) and reducing environmental impact while maintaining products of quality. A daily task schedule for machines, implements, drivers, and controllers should be generated at the beginning of each work shift, usually each morning. However, the possibility of execution of some tasks depends strongly on the weather conditions that may change during the day. The quantity of irrigation water, pesticides or fungicides, or herbicides depends also on weather conditions. Thus, a planning and scheduling solution method must be dynamic, producing a farming schedule that is adaptable in real-time.

The objective is to optimally allocate the agriculture machinery system to a set of given tasks in a rolling horizon, responding dynamically to unpredicted contingencies and considering route congestion and the constraints of each one of the actors in this problem. Each task requires a tractor-implement combination, and in case of traditional tractors, also including a driver capable of operating with that combination on a given task. In the allocation process, the best *vehicle-implement-driver (VID)* combination should be found at the global level while considering each task's requirements and its time and space of allocation. The VID combination should be routed through the field considering congestion on the farm or road, and it should be reconfigured when necessary considering both overall system performance, weather conditions and individual task, driver, implement and vehicle requirements. Tasks may need specific weather conditions while some tasks may be more important than others.

Implement parameters usually include: maintenance frequency (maximum time and distance passed in operation between two maintenance activities), operation state (damaged, operating), efficiency level for each task, task compatibility (an implement can perform a subset of tasks), tractor compatibility (it can be installed on a subset of tractors) and potentially implement cleaning (to avoid cross-contamination of diseases across fields).

Tractor parameters include: maintenance and cleaning frequency, operation state, task compatibility and compatibility with implements and related requirements (power, weight, front power take-off (PTO) used for taking power from a power source, guidance system or not, front loader, specific tires, etc.), driver requirements, fuel autonomy, and type and number of operators needed for operation per each task. Human operator parameters include: operation status (available, unavailable), daily and weekly work hours and breaks (accumulated, required), task preferences/specialisations and mobility limitations (by car, walking).

The overall objective is for the agriculture vehicle fleet to dynamically (re-)allocate the vehicle-implement or vehicle-implement-driver combination for each task and to route the combination through dynamically changing tasks considering vehicle, implement, driver, maintenance and charging constraints while minimising the overall cost of the fleet's operation.

5 Related standard combinatorial optimisation problems and solution approaches

In this section, we research standard combinatorial optimisation problems that provide a baseline for the coordination problem applied to agriculture fleets, as described previously. We concentrate on the dynamic versions of these problems, that is, the case when both task demand and resource availability may vary in time.

The most important decisions that must be taken by fleet managers have to do with the problems of assigning agriculture vehicles to implements and tasks (e.g. [31]) and managing their routes (e.g. [7, 9, 18, 46, 48, 49, 64, 65]). Emmi [16] proposes a control architecture to integrate a vehicle equipped with a farm implement, with the purpose of constituting a fully autonomous agricultural unit able to work cooperatively in a fleet of robots. To achieve this aim, characteristics of the required configuration are identified, complying with specifications of hardware reliability, modularity, expandability, ergonomics, maintenance and cost, for the purpose of providing manufacturers of agricultural machinery with solutions for automating new developments in precision agriculture. The results obtained, both qualitative and quantitative, confirm the validity of their proposal.

An example of a centralised coordination model of a multi-agent architecture is a centralised entity OptiVisor that coordinates a Mobile Agricultural Robot Swarm (MARS), presented in [8]. OptiVisor is responsible for path planning, optimisation and supervision of MARS and serves as a mediator between the robots and different cloud services.

The problem of assignment (dispatch) is to decide a vehicle to be assigned to each task. Conventionally, vehicles are assigned to tasks based on the First Come, First Served (FCFS) strategy. This strategy creates great discrimination among the tasks, increases transport costs and significantly lowers overall fleet performance. Fleet management significantly improves if the vehicles are dynamically assigned (in real time) depending on the characteristics of each vehicle and task requirements (e.g. [5, 10, 30, 55].

Various mathematical and computational models have been developed for the optimisation of fleet operations to serve customer demands while minimising costs, e.g. [4, 13, 30, 40, 41, 43]. Many of the problems of fleet management correspond to combinatorial optimisation problems, such as the problem of determining optimal routes e.g. [10, 13, 30, 35, 41, 43], that are still very difficult to solve, even in a static context with batch processing of requests and dynamic vehicle assignment problems, e.g. [25, 31, 44].

In the case of poor fleet performance, a penalty for non-compliance with Service Level Agreements (SLAs) translates into the loss of revenue. For agri-robot fleets, optimal allocation of tasks and well-designed routes to agri-robots not only ensure the service level, but also meet the needs of the fleet owner and stakeholders in a cost-effective and efficient manner. Nowadays, the assignment of agriculture machinery and agri-robots to crop tasks is still mostly done by human experts (e.g. [23, 67]).

5.1 Multi-index assignment problem

The methods for dynamic agri-robot fleet task assignment are relevant in various scenarios, e.g. emergency services [5, 31, 32, 55], taxi, hot meal home delivery and vehicle sharing. We believe that a combination of these methods can provide a true differential value for agri-robot fleets.

The problem of allocation of the vehicles to implements and indivisible tasks may be modelled as a *multi-index assignment problem* [45] that we re-run in each time period when the constituents of the problem change. Each constituent part of this allocation is characterised by a set of attributes describing its availability and compatibility with the rest of the constituents that influence the cost or profit resulting from such a multi-index allocation. Assume there are n vehicle agents, m tasks and k implements. Here, the emphasis is on one-on-one assignment among the elements in each set. Furthermore, each vehicle agent has a valuation function that maps each implement-task combination to some non-negative value particular to that vehicle agent. These valuations are additive, which means that an agent's value for a set of task-implement combinations is simply the sum of the values of each combination of this set. Our goal is to compute a one-on-one allocation, i.e. a partitioning of m tasks, k implements and n vehicle agents, of minimum overall cost.

The mathematical formulation of such a problem leads to *axial k-index assignment problems* [47] and in the case of three indices (vehicles, implements and tasks), to the *axial 3-index Assignment Problem (axial 3AP)*, which is an NP-hard binary programming problem for which the only scalable and efficient solution approach is based on (meta-)heuristics (e.g. [62]). Moreover, no polynomial-time algorithm can achieve a constant performance ratio for this problem unless P = NP [12]. Crama and Spieksma designed approximation algorithms that yield a feasible solution whose value is not worse than 3/2 of the optimal value when the overall assignment cost is a decomposable sum of the costs of all the three set pairs [12].

Reynen et al. [52] present alternate integer programming formulations for the multi-dimensional assignment problem with decomposable costs with an increased number of variables and present solution methods based on Lagrangian Relaxation and massively parallel algorithms. Aiex et al. [1] designed a greedy randomized adaptive search procedure with path relinking (GRASP) for solving axial 3APs. GRASP is a multistart metaheuristic for combinatorial optimization consisting of a construction procedure based on a greedy randomized algorithm and a local search. A parallel version appeared in [39]. Their computational experiments showed very good results compared with previously proposed heuristics. Huang and Lim [24] proposed a hybrid genetic algorithm for this problem and reported on extensive computational experiments. Li et al. [29] propose a novel convex dual approach to the three-dimensional assignment problem. It is shown that the proposed dual approach is equivalent to the Lagrangian relaxation method in terms of the best value attainable by the two approaches. However, the pure dual representation is not only more elegant, but also makes the theoretical analysis of the algorithm more tractable.

An asymptotical optimal approximation algorithm for axial k-index assignment problems was given by Kravtsov [27]. Frieze et al. [19] study random multi-dimensional assignment problems where the costs decompose into the sum of independent random variables. They minimise the total cost and show that with high probability a simple greedy algorithm is a $(3+O(1))$-approximation. An adaptive algorithm that extends the basic greedy-type algorithmic schemes using transition to a probabilistic setup based on variables randomisation for solving the axial 3-Index AP was also proposed [38]. Here, the minimisation of an objective function is replaced by the minimisation of its expectation.

5.2 Assignment problem

The multi-index assignment problem is a higher dimensional version of the standard linear (two-dimensional) assignment problem, i.e. a weighted bipartite matching problem in which the objective is to minimise total cost of assigning n resources to n tasks. The latter is an important subproblem of many NP-hard optimisation problems, e.g. Traveling Salesperson Problem, for which both sequential (Hungarian algorithm, shortest path algorithms and auction algorithms) and parallel implementations of these algorithms are known.

In the case where sets of fixed vehicle-driver-implement combinations are static and given in advance, each such combination can be considered as an agent. Then, the *multi-index assignment problem* is simplified to the *assignment* problem focusing on the one agent-one task allocation at the time (e.g. [6, 32]).

The dynamic task assignment problem is equivalent to the assignment problem for which several centralised approaches exist, e.g. [40]. One of the best known is the Hungarian method [28]. In [21], Lujak et al. proposed a distributed version of the Hungarian Method for multi-robot task allocation where mobile robot agents are required to store all the information locally and there is no available shared memory. One of the tools for mechanism design of agent systems are auctions, e.g. [3, 33, 54]. Schneider and colleagues [56, 70] studied task allocation in the context of multi-robot teams and evaluated the efficacy of auction-based mechanisms when implemented on simulated and physical robots. This work highlights the levelling effects of real-world constraints, such as collision avoidance, which tend to minimise the differences between allocation mechanisms.

The implementation usually requires solving a combinatorial nonlinear optimisation problem, which is in general NP-hard and intractable for complex networks. However, with certain relaxations, the latter can be modelled as a convex optimisation problem [3, 42]. Computational optimisation auctions are methods that are similar to the Gauss-Seidel and Jacobii methods, e.g. [3]. This approach is well suited for massive parallelisation of local decision-making based on the information interchanged among multiple processors. It is modular, based on regular interactions, incremental, analysable, and permits incentive engineering. In [33, 34], Lujak et al. proposed a modified version of Bertsekas' auction algorithm for the case of incomplete information exchange and explored the deterioration of the solution quality according to the size of the communication network and proposed strategies to overcome this problem. Responding to the task assignment in the case of the medical emergency assistance of emergency patients by ambulances, Lujak et al. proposed a distributed algorithm for the simultaneous assignment of ambulances [5, 31] and ambulances and hospitals to multiple simultaneous patients in [32], where the authors also proposed an ambulance vehicle Voronoi-based relocation approach. Through a dynamic vehicle reassignment, we can significantly increase the overall performance of the fleet and lower farming costs.

6 Open issues and research opportunities

Agri-robot fleets are intrinsically decentralised systems. They comprise a number of geographically distributed agri-robots capable of communicating with each other and possibly with fixed infrastructure sensors on the field and/or with human collaborators. Traditionally, distributed systems refer to systems consisting of sequential processes (each one with an independent thread of control, possibly located on geographically distributed processors) that coordinate their actions by exchanging messages to meet a common goal (e.g. [20, 63]).

Distributed MAS-based route guidance for agri-robot fleets that reach towards completely autonomous fleets is still an open scientific question. The topic of distributed and dynamic multi-task assignment and vehicle routing considering multiple vehicle, operator and farming constraints is still an insufficiently explored field. To the best of our knowledge, distributed and decentralised MAS coordination models and optimisation approaches for vehicle fleet coordination are scarce and have undergone limited testing.

In this paper, we have discussed the levels of decentralizing coordination of agri-robot fleets, from centralized over distributed, to the decentralized coordination models. Depending on the vehicle ownership context, a distributed or decentralized MAS may be applied; if there is only one fleet owner, we speak about the distributed case. Otherwise, the decentralized case applies. The distributed and decentralized coordination models are more robust than their centralised counterparts because they are resilient to individual vehicle errors and can rely on their intrinsic built-in redundancy. They are scalable since they can operate at a larger scale and assist more fields at once aggregating vehicle capacity and field throughput across all the fleet's vehicles. They are open, seamlessly adapting to vehicles entering or leaving the system, and they have fewer levels of authority. Finally, they do not suffer from the "single point of failure" problem found in centralised systems. However, distributed open vehicle fleets also have to deal with inter-agent communication and coordination overhead that can sometimes make them slower or more difficult to control than their centralised counterparts. The decentralized fleets, on the other hand, lack the guarantees on solution quality.

Following a decentralized solution approach, the agriculture vehicle fleet coordination problem combines the aspects of the assignment problem, 3-index assignment problem and vehicle routing problem. There are multiple centralised algorithms that work for each of these individual subproblems assuming perfect information, but to the best of our knowledge, both the mathematical formulation for the overall agriculture vehicle fleet coordination problem and the related solution approach are still open challenges.

In the decision-making distribution process, the emphasis of the decomposition of the MAS coordination problem should be on the scalability, local communication and computation constraints of each physical vehicle agent, the structure and topology of the dynamic communication network, and the available communication and processing capacities of the developed cyber-physical MAS. One common goal in this context is an efficient and cost-effective farming service using an agriculture vehicle fleet while considering vehicle autonomy and fairness constraints in work assignment, individual rationality, preferences and constraints whether it is of operators, farmers or fleet owner(s), as well as farming tasks' constraints. Quality of solution guarantees play a crucial role underlying sustainable competitive advantage.

The long-term goal of distributing decisions in agriculture vehicle fleets is the development of an open and non-proprietary software platform in a cloud for distributed route guidance and task coordination at large agriculture farms and peer-to-peer sharing of relevant agriculture resources, vehicles and agri-robots among farmers. Such an agri-robot fleet coordination approach contributes to a more efficient and competitive service in line with the Internet of Robotic Things (e.g. [57]) and Internet of Food Things [58]. Human drivers may also benefit from this technology as they may be motivated to perform better if they feel a sense of autonomy, thus improving the output, task engagement, time-on-task and accuracy. However, behavioural measures should be further studied to understand the triggers of individual effort and motivation.

Even though scalable coordination mechanisms are essential for efficiently managing large-scale distributed and decentralized agri-robot fleets, it should be noted that, for real-world applications, they need to be complemented with other technologies. In particular, semantic mismatches among agents need to be dealt with through the alignment of ontologies, so agents can reach a common understanding about the elements of coordination. In addition, trust and reputation models are necessary for keeping track of whether the coordination plan and its execution respect the requirements defined *a priori*.

The indirect benefits of such a distributed or decentralised agri-robot fleet coordination MAS (depending on the vehicle ownership context), among others, should include higher efficiency and benefit in large farms, smaller carbon footprint and reduction in pesticides, and above all, fair participation of fleet owners, agri-robot operators and farmers with related rewards and benefits. Decentralised coordination mechanisms may not fix the sustainable agriculture concerns, but they should improve them as they are directly related to giving higher autonomy to the vehicle fleet while changing the hierarchical and unscalable farming structure to a more efficient balanced one.

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